Disposed to Be Overconfident

Katrin Gödker, Terrance Odean, and Paul Smeets*

September 25, 2024

ABSTRACT

We hypothesize that individuals learn about their investment ability based on realized gains and losses rather than overall portfolio performance. Thus, how investors sell their stocks, or how they remember those sales, impacts their confidence. The disposition effect and self-serving memory leads to investor overconfidence. We provide empirical evidence for this in (i) survey data and transaction records of Dutch retail investors and (ii) an experiment for causality. In a final step, we outline a model that formalizes the learning mechanism and how it leads to overconfidence as well as lower trading profits and higher volume.

JEL classification: D01, G4
Keywords: Investor Beliefs, Overconfidence, Disposition Effect, Selective Recall, Experiment

*Katrin Gödker: Bocconi University, CESifo, katrin.goedker@unibocconi.it; Terrance Odean: Haas School of Business, the University of California at Berkeley, odean@berkeley.edu; Paul Smeets: University of Amsterdam, p.m.a.smeets@uva.nl.
We are grateful to Lawrence J. Jin for his valuable input. We thank Brad Barber, Kai Barron, Stefano Cassella, Sebastian Ebert, Carlo Favero, Cary Frydman, Nicola Gennaioli, Simon Gervais, Andrej Gill, Sam Hartzmark, Paul Heidhues, Zwetelina Iliewa, Mats Köster, Steffen Meyer, William Mullins, Pietro Ortoleva, Michaela Pagel, Cameron Peng, Julien Sauvagnat, Philipp Strack, and Roberto Weber for very helpful comments and suggestions and Francesco Bilotta and JD O'Hea for great research assistance. We thank seminar participants at the Berlin Behavioral Economics Seminar, CEPR Advanced Forum in Financial Economics (CAFFE) seminar series, CEU Vienna, Cheung Kong Graduate School of Business, ESSEC Business School, Innsbruck University, LMU Munich, NYU, Radboud University, São Paulo School of Economics, and participants at the CESifo Area Conference on Behavioral Economics 2023, Citrus Finance Conference at UC Riverside, DFG (Deutsche Forschungsgemeinschaft) Workshop on Consumer Preferences, Consumer Mistakes, and Firms' Response at Frankfurt School 2024, Experimental Finance Conference 2022, Helsinki Finance Summit 2022, IZA Beliefs Workshop 2024, Journal of Investment Management Conference 2023, Research in Behavioral Finance Conference (RBFC) 2022, SAFE Household Finance Workshop 2021, SITE Conference 2022, SFS Cavalcade 2022, WFA 2022, and Zurich Workshop on Economics and Psychology 2023 for helpful comments.

I. Introduction

How do investors learn about their ability? Investment skill is difficult to evaluate. Even academics disagree about which measures of performance investors do, or should, use (Berk and van Binsbergen (2016); Barber, Huang, and Odean (2016)) when assessing skill. Furthermore, the multi-factor alphas an econometrician might favor require data and statistical analysis not available to most retail investors. We believe that when informally evaluating their investment skill, investors use a metric of past performance that: 1) is cognitively tractable, 2) uses information that easily comes to mind, and 3) is similar to metrics used in other domains of life. Specifically, we argue that investors use a metric that is based on realizations.

For example, suppose that you ask a friend how good their favorite sports team performs this season. One metric they will likely quote you is the team's win-loss record, e.g., the San Francisco Giants baseball team currently has a middling record of 53 wins and 55 losses. For a retail stock investor, an analog to this win-loss record is the number of stocks they sold for a gain versus the number of stocks sold for a loss. Retrieving these two numbers from memory and comparing them is cognitively easy. Furthermore, for the investor who trades occasionally, realized gains and losses are likely to be more salient than daily price movements in their portfolio (Frydman, Barberis, Camerer, Bossaerts, and Rangel, 2014).

This realized gains vs realized losses metric is appealing, but imperfect. One shortcoming is that the metric discards information from unrealized gains and losses and is thus vulnerable to two pervasive biases: i) Investors are likely to realize gains more readily than losses relative to opportunities, that is, investors are likely to have a disposition effect (Shefrin and Statman, 1985; Odean, 1998a; Weber and Camerer, 1998; Frazzini, 2006)[1]; ii) Investors are likely to misremember their realized gains and losses in a self-serving fashion (Gödker, Jiao, and Smeets, forthcoming). This paper documents how such a biased metric can lead investors to form positively biased beliefs about their abilities.

We first show that net realized gains (i.e., the number of realized gains minus the number of realized losses) predict the self-assessed relative performance of Dutch retail investors even after controlling for actual relative performance. Our field evidence is based on portfolio and trading records of retail investors at a Dutch financial institution as well as a survey conducted among these retail investors. We show that investors who realize more gains than losses believe they have higher annual portfolio performance relative to other investors, even after controlling for actual annual portfolio performance. Further, we document that retail investors selectively recall their realized gains and losses. They recall a higher number of gains than actually realized, but do not significantly misremember losses. Thus separately or together the tendencies

[1]The disposition effect has been found in the United States, Israel, Finland, China, and Sweden by Odean (1998a), Shapira and Venezia (2001), Grinblatt and Keloharju (2001), Feng and Seasholes (2005), and Calvet, Campbell, and Sodini (2009). It is also documented for the real estate market and the option market by Genesove and Mayer (2001) and Heath, Huddart, and Lang (1999).

to realize gains more readily than losses and to remember gains for readily than losses leads investors who use net realized gains as a performance metric to overestimate their past performance. Overestimating past performance can lead to overconfidence about ability and future performance.

While this analysis documents a positive correlation between net realized gains and how investors rank their own abilities, it does not establish causality. The correlation may be due–as we claim–to investors using net gains as a measure of their ability. However, it is also possible that an unobserved trait—such as the desire to maintain a positive self-image—leads some investors to realize more gains (remember more gains) and rank themselves more highly.

To explore causality, we run an experiment. In our experiment, subjects participate in two trials of an investment task. The task has five investment periods. At the beginning of the first investment period, subjects choose an initial portfolio of five risky stocks from a group of twenty. Stocks differ in quality and stock prices change stochastically. There are two types of stocks, a high type and an ordinary type, which differ in the probability of experiencing a price increase or decrease each period. Subjects do not directly observe stock types but can make inferences from previous price changes. After observing three prior price changes for each of the twenty stocks, subjects choose five stocks. At the beginning of each subsequent investment period, one of the stocks in each subject's portfolio is sold automatically by the computer. The subject then purchases a stock from a newly generated set of four stocks for which the subject also observes three prior price changes. At the end of each period, stock prices change stochastically. Thus subjects hold five stocks in their portfolio throughout the task which ends at the end of five investment periods.

We test for the causal effect of gain or loss realizations on subjects' beliefs about their ability to choose high-type stocks. To do so, we exogenously manipulate whether subjects sell for a gain or loss. By exogenously imposing sales, we avoid the possibility that an unobserved psychological mechanism is both driving the decisions to realize gains or losses and subjects' confidence in their ability. We impose two conditions. In the *Selling Gains* condition, a winning stock—a stock whose current price is above its purchase price—is randomly selected and sold. In the *Selling Losses* condition, a losing stock is randomly selected and sold.[2] We randomly assign subjects to one of these two conditions. Each subject is assigned to the same condition for both task trials. For stocks in their portfolio, subjects observe both realized gains and losses as well as paper gains and losses each period. At the end of the final period, we measure subjects' self-reported confidence in their ability to select high-type stocks.

The experiment has four main findings. First, after making investment choices and observing outcomes, subjects in the *Selling Gains* condition are more confident than subjects in the *Selling Losses* condition that

[2] If the portfolio has no winning stocks in the *Selling Gains* condition or has no losing stocks in the *Selling Losses* condition, then an arbitrary stock is randomly selected and sold.

they would outperform most other subjects if the trading experiment were repeated. Second, subjects form beliefs about their ability to select high-type stocks based on realized gains and losses rather than overall portfolio performance (including unrealized gains and losses). Third, the treatment effect on confidence is of similar magnitude to a gender effect on confidence, which has been documented to be a meaningful predictor of investor overconfidence in many studies. Fourth, after making investment choices and observing outcomes, subjects in the *Selling Gains* condition are *over*confident. They significantly overestimate their ability relative to others, which is in line with the "better-than-average effect" (Moore and Healy, 2008) and believe that they have selected significantly more high-type stocks than they actually have, which is in line with overplacement (Moore and Healy, 2008). In reality, subjects in both treatments select, on average, a similar number of high-type stocks (5.80 in the *Selling Gains* and 5.76 in the *Selling Losses* treatment (t-test, $p = 0.873$)).[3]

The experiment is designed to identify the causal effect of gain/loss realizations on subjects' confidence levels. It is worth noting that it is not designed to test whether investors exhibit the disposition effect, which is well established (Odean, 1998a), or why. Previous studies have offered several explanations for the disposition effect. We discuss the most prominent explanations in Appendix C. These explanations rely on preferences, emotions, beliefs, or institutional factors (e.g., transactions costs). Our documented learning mechanism is not dependent upon the reason why people exhibit a disposition effect.

To formalize the investors' biased learning process and its implications, we develop a theoretical model. In line with our empirical results, the model makes the critical assumption that investors form their beliefs about their investment ability by counting the number of gains and losses they have realized. The model considers two types of investors: a high ability investor whose ability to choose stocks is high, and a low ability investor whose ability to choose stocks is low. Investors vary in how strong their metric is biased. The model produces three predictions. First, investor overconfidence increases with investors' biased learning input: investors who are more likely to realize gains than losses overestimate their abilities to select stocks. This result is consistent with the findings from our field evidence and experiment. Second, the effect on overconfidence is greater for low ability investors. Third, investor overconfidence, generated by the biased learning process, leads to both excessive trading and lower trading profits.

Why is it important to study how investors learn about their ability? A large empirical and theoretical literature argues that retail investors are overconfident. They systematically believe that their own investment ability is better than it actually is. In theoretical settings, experimental markets, and actual markets, overconfident investors trade more than is in their own best interest and contribute to price volatility (Odean, 1998b; Deaves, Lüders, and Luo, 2009; Barber and Odean, 2001; Daniel and Hirshleifer, 2015). Thus under-

[3]Subjects' profit from the investment task was also similar across treatments (t-test, $p = 0.957$).

standing the mechanisms that increase investor overconfidence may lead to improvements in investor welfare and to a better understanding of market dynamics.

Most studies in financial economics treat investor overconfidence as a static personal trait and do not examine the processes through which investors become more—or less—overconfident. The economics literature on motivated reasoning investigates overconfidence in a more dynamic way. Several papers argue that people derive utility from overconfidence and other self-serving beliefs (Bénabou and Tirole, 2002; Köszegi, 2006; Brunnermeier and Parker, 2005). Consistent with these studies, recent experimental work provides evidence that people become overconfident by forming and updating optimistic beliefs in ego-relevant domains, such as intelligence (Zimmermann, 2020), beauty (Eil and Rao, 2011), and generosity (Saucet and Villeval, 2019; Di Tella, Perez-Truglia, Babino, and Sigman (2015); Carlson, Maréchal, Oud, Fehr, and Crockett, 2020). In this paper, we document a learning process that increases investor confidence about their ability to invest. If investors realized gains and losses proportionately to opportunities and remembered realizations accurately, the net realized gains metric would be unbiased (though not optimal). However, most investors display a disposition effect and most have self-serving memory bias. Because these biases are widespread, their effect on investors' self-assessment is likely to be systematic and to influence mean self-assessments. Thus most investors will rate themselves as above average and, in aggregate, be overconfident.

Our study is closely related to the theory of Gervais and Odean (2001), who argue that investors attribute positive portfolio performance to their own ability rather than luck and become overconfident.[4] The innovation of our study is that we show that investor overconfidence is not only influenced by past performance but by how investors evaluate and *perceive* their past performance. We propose a distinct learning process in which investors assess their ability by counting their number of realized gains and losses. Thus perceived performance can differ substantially from actual performance and separately influence the beliefs investors form about their ability.

Many behavioral finance papers focus on a single bias or behavior, yet biases and behaviors can interact in ways that magnify or offset their effects (Barberis and Thaler, 2003; Benjamin, 2019).[5] We document a biased learning mechanism through which the disposition effect as well as selective recall can lead to investor overconfidence. Thus, how investors sell their stocks, or how they remember those sales, matters for their confidence levels.

This link between the disposition effect and investor overconfidence could help explain why retail investors tend to re-invest more after realized gains and tend to reduce their risk and stock market participation after

[4] Barberis and Thaler (2003) conjecture that overconfidence may also arise from hindsight bias, but they do not provide tests of this conjecture.

[5] There are few studies in economics examining how biases can affect overconfidence. For instance, Bénabou and Tirole (2002) investigate the interaction between individuals' present bias and overconfidence and Jehiel (2018); Barron, Huck, and Jehiel (2024) study the interaction between individuals' selection neglect and overconfidence.

realized losses (Meyer and Pagel, 2022). In addition, the connection between the disposition effect and investor overconfidence suggests that reducing the disposition effect might also reduce overconfidence. Thus interventions that have been shown to decrease the disposition effect through using limit orders (Fischbacher, Hoffmann, and Schudy, 2017), decreasing the salience of purchase price (Frydman and Rangel, 2014), and transferring or "rolling" assets (Shefrin and Statman, 1985; Frydman, Hartzmark, and Solomon, 2018), could mitigate investor overconfidence.

Our results contribute to the large literature on the influence of attention on belief formation. It is often argued that more attention improves belief accuracy and subsequent decision quality (see Gabaix (2019) for review). In contrast, others argue that in some situations – if greater attention is combined with an incorrect mental model of the problem – attention can lead agents to overweight specific features of the decision problem relative to the normative benchmark when updating beliefs (Dawes, 1979; Dawes, Faust, and Meehl, 1989). For example, Hartzmark, Hirshman, and Imas (2021) have recently shown that people focus and react more strongly to signals about the quality of a good when they own it. We document that when people own a good, in our case an investment, they focus on a subset of signals, namely the realized gains and losses, when updating about the quality of the investment and when assessing their ability to select high-quality investments.

Our paper adds to a literature that examines how past experienced outcomes affect subsequent investment decisions and risk taking behavior (Thaler and Johnson, 1990; Weber and Camerer, 1998; Kaustia and Knüpfer, 2008; Choi, Laibson, Madrian, and Metrick, 2009; Strahilevitz, Odean, and Barber, 2011; Malmendier and Nagel, 2011; Campbell, Ramadorai, and Ranish, 2014; Imas, 2016; Kuhnen, Rudorf, and Weber, 2017; Du, Niessen-Ruenzi, and Odean, 2024). In particular, Imas (2016) documents that a 'realization effect' in prior losses and gains can affect future risk taking: Following a realized loss, individuals avoid risk; following the same loss that has not been realized individuals take on greater risk. One limitation of this literature is that it often does not clearly identify whether past experiences affect future behavior through a beliefs, emotions, or preferences channel. We show that investors' prior gain and loss realizations directly causally affect their beliefs about their investment ability.

How investors measure their ability is likely to depend on how actively they trade. In our Dutch retail data and our experiment, the number of realized gains versus losses matters. Investors who trade much more actively might aggregate trading outcomes. For example, Brazilian day traders respond to the number of days on which they were or were not profitable (Chague, Giovannetti, Guimaraes, and Maciel (2023)). Given the large number of trades made by many day traders, counting days is likely more cognitively tractable than counting the number of profitable or unprofitable trades.

The paper proceeds as follows. Section II outlines our field evidence for Dutch retail investors based on survey results and individual-level transaction analyses. Section III describes the experimental design and discusses our main findings. Section IV presents a theory and analyzes its implications. Section V concludes. Additional details of the experimental instructions are in the Appendix.

II. Evidence from the Field

We analyze a unique data set that links confidence measures from an online survey among Dutch retail investors to their actual realizations and performance from individual portfolio and trades data.

A. *Investor Portfolio and Trades Data*

We obtain individual portfolio and transaction-level data of the financial institution's retail clients. The portfolio data include quarterly holdings during the period of January 01, 2013 to May 31, 2020 and monthly portfolio returns during the period of January 01, 2013 to May 31, 2020. The portfolio level return includes the return of all investments in the respective account. Our trades data include information on each transaction executed in the clients' investment accounts during that period, including date and time, asset ID (ISIN), price in Euros, number of shares, and type of transaction. The study is limited to common stocks for which this information is available. Multiple buys or sells of the same stock, in the same account, on the same day, are aggregated.

Investors' performance. Based on each retail client's monthly portfolio returns in 2019, we calculate the geometric average annual return in 2019. We then calculate for each client a performance-based percentile rank, which we calculate based on their annual portfolio return in 2019 compared to all other retail investment clients' annual portfolio return in 2019 at that financial institution (*Actual Percentile Rank*).

Investors' realizations. We calculate client's realized gains and losses based on their trading records and count them. Each day that a sale takes place in an investor's portfolio of at least two stocks, we compare the selling price of each stock sold to its weighted average purchase price to determine whether that stock is sold for a gain or a loss. The weighted average purchase price is calculated based on previous purchases of that specific stock made by the investor during the time period of our data set (January 01, 2013 to May 31, 2020). If there is no corresponding purchase in our data, no realized gain or loss is counted. We adjust for stock splits if stock splits occurred. We obtain information on stock splits from FactSet. We calculate the difference between the number of realized gains and losses (*Net Gains*):

$$\textit{Net Gains} = \text{Realized Number of Gains - Realized Number of Losses.} \tag{1}$$

A positive difference indicates that the investor realized more gains than losses; a negative difference means that the investor realized fewer gains than losses; a zero difference indicated that the investor realized the same number of gains and losses.

For clients who participated in the survey, we can link the portfolio and transactions data to the client's survey responses at the individual level using a pseudoanonymized identification number. We limit our analysis to investment accounts that are i) in the name of the respective survey participant and ii) allow for own execution of transactions (rather than investment accounts managed by the institution). If a survey participant holds more than one investment account that satisfy these criteria, we merge the accounts.

B. Survey Data

We conducted an online survey among clients of a Dutch financial institution.[6] The survey was sent out to the financial institution's retail clients aged 18 years or older holding an investment account at the financial institution, excluding very high net worth individuals and those who did not want to be contacted by email. In total, we sent the survey to 120,865 clients. The survey took about 15 minutes to complete and by participating respondents had a chance of winning 300 EUR. In addition, the questionnaire contained incentivized tasks and questions that gave participants the chance of winning extra money, up to an amount of 120 EUR extra. 5,282 clients completed the survey (response rate of 4.4%). The survey was conducted between July 1, 2020 and July 16, 2020. The survey consisted of the following parts: 1) introductory questions for screening, 2) confidence elicitation and elicitation of recalled realizations (in randomized order), 3) questions about decision-making style and financial knowledge, 4) elicitation of risk perception, 5) questions about demographics. Our analyses in this paper use clients' responses to two survey questions as key variables.

Investors' beliefs about performance (confidence level). We measure clients' beliefs about their relative investment performance by asking for self-reported portfolio performance relative to other retail investors in the year before the survey, 2019. In particular, we ask survey participants to indicate an estimate of the percentage of retail investors at the financial institution who achieved a higher annual portfolio return in 2019 than themselves (between 0% and 100%). We use this response to calculate the respondents' performance-based percentile rank among the financial institution's retail clients by subtracting the reported percentage from 100 (*Elicited Percentile Rank*).

Investors' recalled realizations. We elicit clients' recollection of their realizations in 2019 in an incentivized way. Survey participants could earn 10 EUR for each recall question they answered correctly.

[6] The survey and its procedure were approved under ethical approval code ERCIC_187_06_05_2020 by the Ethical Review Committee Inner City Faculties (ERCIC) of Maastricht University. We obtained subjects' informed consent before they participated in the survey.

We ask survey participants how many stocks they sold for a gain in the year 2019. We explain to participants that "selling for a gain" means selling for a price higher than the average purchase price of that stock. Participants are asked to indicate the number of stocks sold for a gain. Similarly, we ask survey participants how many stocks they sold for a loss in the year 2019. We explain to participants that "selling for a loss" means selling for a price lower than the average purchase price of that stock. Participants are asked to indicate the number of stocks sold for a loss. We ask them to indicate their answers without looking up their actual sales online. We calculate the difference between the recalled number of realized gains and losses (*Recalled Net Gains*):

$$\textit{Recalled Net Gains} = \text{Recalled Number of Gains - Recalled Number of Losses.} \tag{2}$$

A positive difference indicates that the investor recalls more gains than losses; a negative difference means that the investor recalls less gains than losses; a zero difference reflects that the investor recalls exactly the same number of gains and losses. If an investor did not report any sales in 2019, we drop this observation from the analysis.

C. Sample Demographics and Summary Statistics

Table I reports descriptive statistics for our survey participants. We limit our sample to investors who i) responded to the confidence question in the survey and ii) can be linked to portfolio and trade data (1,540 investors). We further exclude observations if the participant's recalled number of realizations deviates by more than +/- 20 from participant's number of total sales in 2019 according to their trading records, which results in a sample of 1,479 retail investors. This investor sample made 8,314 transactions in 2019, i.e., on average each investor made 5.62 trades in 2019. 11% of the sample is female and 89% of the sample is male. On average, survey participants were 55.10 years old (min. 18 years). Our investor sample holds average portfolios of the size of 35,588.52 Euro. The investors earned an average annual portfolio return of 34.70% in 2019. The average elicited percentile rank of investors' portfolio performance in 2019 is 55.70 and the average actual percentile rank is 54.70 (relative to all other retail clients, not only other survey participants). Investors realized on average 1.41 gains and 0.53 losses in 2019. The Net Gains are on average 0.88. Investors recall, on average, that they realized 4.22 gains and 0.82 losses, with recalled Net Gains of 3.40 on average.

D. Results

The results based on our field data provide supportive evidence for the experimentally documented realization effect on investors' level of confidence.

Table I. Descriptive statistics for survey participants.

	Investor sample (N = 1,479)		
	Mean	Median	St. Dev.
Female	0.11	0.00	0.31
Age (in years)	55.10	57.00	14.48
Stock portfolio size (in Euro)	35,588.52	16,860.87	51,321.14
Annual portfolio return (in 2019, in %)	34.69	20.37	447.57
Actual percentile rank (in 2019)	54.70	53.40	32.91
Elicited percentile rank	55.70	50.00	23.21
Number of transactions (in 2019)	5.62	1.00	19.21
Net Gains	0.88	0.00	3.58
Recalled Net Gains	3.40	2.00	5.23

Result 1. *Retail investors who realized more gains than losses during a year, self-report higher performance relative to other investors during that year after controlling for actual performance.*

Table II provides coefficients from linear regression estimates of investors' beliefs about their performance-based rank among other retail investors (*Elicited Percentile Rank*). As explanatory variables, the models include investors' difference in the number of gains and losses realized (*Net Gains*) as well as their recollection of it (*Recalled Net Gains*). We restrict our analysis to investors who at least had one realization in 2019. The results are robust to restricting the sample to investors who at least had two realizations in 2019 (see Appendix D). We control for investors' actual performance-based percentile rank among all retail clients at the financial institution (*Actual Percentile Rank*). In addition we control for the order of elicitation of the two survey measures, i.e., whether participants were first asked to recollect their realized gains and losses and then about their annual portfolio performance relative to other retail investors or in opposite order. In total, 415 of the 1,479 survey participants responded to the recall questions (28.1%).

The results in column 1 show that participants form their beliefs about own performance relative to others based on the number of realized gains versus losses. The coefficient is significantly positive ($p < 0.001$). The more gains rather than losses an investor realized, the higher the investor's confidence measured by the self-reported performance-based percentile rank. This finding holds when controlling for the investor's actual performance-based percentile rank (column 2). Each additional realized gain over a realized loss increases an investor's percentile rank belief by 0.36 ($p < 0.05$).

Result 2. *Selective recall of realized gains is associated with even higher self-reports of performance relative to other investors.*

Table II. Beliefs about own performance of Dutch retail investors. This table contains the coefficients and robust standard errors (in parentheses) of OLS regressions. The dependent variable is the investors' beliefs about their performance-based rank among other retail investors, *Elicited Percentile Rank*, (between 0 and 100). *Net Gains* is the difference in the number of investors' realized gains and losses in 2019. *Recalled Net Gains* is the difference in the recalled number of investors' realized gains and losses in 2019. *Actual Percentile Rank* is investors' actual percentile rank among all retail clients at the financial institution based on annual portfolio performance in 2019 (from 0 to 100). *Order of Elicitation* is a dummy variable indicating the order in which our two survey items were elicited (1 = recall of realizations first and 0 = otherwise). *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) Elicited Perc. Rank	(2) Elicited Perc. Rank	(3) Elicited Perc. Rank	(4) Elicited Perc. Rank
Net Gains	0.487***	0.362**		
	(0.15)	(0.15)		
Recalled Net Gains			0.726***	0.625***
			(0.17)	(0.17)
Actual Perc. Rank		0.159***		0.133***
		(0.02)		(0.03)
Order of Elicitation				-1.335
				(2.04)
Constant	55.275***	46.685***	55.883***	50.494***
	(0.62)	(1.21)	(1.22)	(3.87)
N	1,479	1,479	415	415
R^2	0.01	0.06	0.03	0.07

Investors in our sample selectively recall their realized gains and losses, which is in line with previous findings from the lab (Gödker et al., forthcoming). As depicted in Table III, investors recall a significantly higher number of gains than actually realized (p < 0.001), but do not significantly misremember losses. This suggests that selective recall can reinforce our documented learning mechanism. Selective recall can bias the metric investors use to assess their ability further towards including more gains than losses, leading to a more optimistic belief about own ability.

Table III. Recall of gains and losses. This table reports t-test statistics for participants' recalled number of realized gains or losses and their actual number of realized gains or losses based on their transaction data.

N = 415	**Mean**	**St. Dev.**	***t*-statistic**
Recalled # of Realized Gains	4.22	5.34	
Actual # of Realized Gains	2.17	4.39	
Difference (Memory Bias)	2.05	3.78	11.02
Recalled # of Realized Losses	0.82	1.77	
Actual # of Realized Losses	0.73	2.12	
Difference (Memory Bias)	0.09	2.04	0.94

Indeed the effect on confidence is stronger if we test for the effect of investors' recalled difference in realized gains and losses – those gains and losses that stick to investors' minds (Table II, column 3 and 4).

Controlling for the actual performance-based percentile rank and order of elicitation, each additional recalled gain over a loss increases investors rank belief by 0.63 ($p < 0.001$).

III. The Experiment

A. *Experimental Design*

To investigate how gain and loss realizations causally affect an investor's belief about her ability to select stocks, we adopt an experimental set-up with (i) a decision that generates investment outcomes, (ii) exogenous variation in realized investment outcomes (gains and losses), (iii) an environment that facilitates learning about own ability, and (iv) a direct elicitation of beliefs about own ability. In this section, we outline these features in more detail. The experiment instructions are provided in Appendix A.

In our experiment, subjects make investment decisions. They participate in two investment task trials of five periods. Before each period t, subjects select the stock(s) to invest in from a set of risky stocks. The purchase price of each stock is the same ($30). Each period, the stock price increases or decreases.

There are two types of stocks, an ordinary type and a high type. These two stock types differ in the probability that their price increases or decreases. An ordinary-type stock has a 40% probability of a price increase and a 60% probability of a price decrease. A high-type stock has a 60% probability of a price increase and a 40% probability of a price decrease. The price change is drawn from $\{-3, -1, 2, 6\}$. In particular, if the price increases, the price change is $2 or $6, with equal probability. If the price decreases, the price change is –$1 or –$3, with equal probability. Subjects are not told which stock is of which type. However, they know the return generating process for the two types of stocks. And, before each choice, subjects view three recent outcomes of each of the stocks from which they select.

Subjects begin with an endowment of $180 and must buy a portfolio of five stocks from a list of 20 available stocks. The list contains exactly 15 ordinary-type stocks and five high-type stocks, which is known to subjects. This gives us enough room to measure overestimation of the number of high-type stocks selected. After the initial portfolio selection, the investment periods (1-5) begin. In periods 1 through 4, subjects (i) observe the period price change for each of the stocks in their portfolio. After the new prices are displayed, (ii) one of the stocks is automatically sold by the computer program at the stock's current price. Subjects accumulate earnings from sales from period to period. After the sale of one stock, (iii) subjects must choose an additional stock to buy from a new list of four stocks. Each new list contains exactly three ordinary-type stocks and one high-type stock, which is known to subjects. Subjects do not know the stocks' types, but observe three previous price changes. In period 5, observe the period price change for each of the stocks in their portfolio but no stocks are sold or purchased. Thus each subject chooses nine stocks to purchase and, for each subject, four stocks are automatically sold in each of the two task trials for a total of eighteen purchases and eight sales.

Importantly, in each period, subjects are provided with information on both realized gains and losses as well as paper gains and losses. Subjects view the information on two separate screens: One screen shows the realized gain or loss from the sale and one screen shows the paper gains and losses of the holding positions (i.e., stocks) in subject's portfolio (see Appendix B).

We follow convention in randomly generating the price paths at the beginning of the experiment for both treatments (Fischbacher et al., 2017). This facilitates between-subject analyses since it reduces noise in response data that stems from different price paths across treatments. We draw seven sets of price paths.[7]

We exogenously manipulate whether the computer sells winning stocks or losing stocks from subjects' portfolios. We have two between-subjects conditions. Subjects are randomly assigned to one of the two conditions. In *Selling Gains*, in each period, a winning stock is liquidated if the portfolio contains at least one winning stock and otherwise a random stock is liquidated. In *Selling Losses*, in each period, a losing stock is liquidated if the portfolio contains at least one losing stock and otherwise a random stock is liquidated. In this experiment, a winning stock is a stock with its current price higher than the initial purchase price of $30, and a losing stock is a stock with its current price lower than the initial purchase price of $30.

Note that we are not inducing a disposition effect–i.e., a preference for selling winners. Rather, by forcing half of the subjects to sell winners, we create patterns of realized winners and losers similar to those generated by the disposition effect.

Further note, because of the momentum in each stock, selling winner stocks can hurt performance in the long run. In our experiment, we all but eliminate this effect by setting a short time period. In actual markets however, the effect can be substantial. Odean (1998a) estimates that stocks sold by retail investors for a gain outperform stocks they continued to hold for a loss, by 3.4% over the next year. This difference in the returns to realized winners and paper losses is likely driven, at least partially, by momentum.

Our main outcome variable is subjects' confidence. We tell each subject to imagine that they are going to participate in another trial of the investment task and we will compare their performance to the performance of 9 other randomly selected people who were invited to participate in this study. We asked subjects to indicate the likelihood that they would be ranked in the upper half of that group (Zimmermann, 2020). With this measure, we elicit subjects' perception of own ability independent of whether they are more or less willing to participate in future investment rounds. This helps to isolate the treatment effect on subjects' confidence levels apart from any treatment effects–such as the house money effect or the realization effect in

[7] That is, we draw seven price sets of 72 stocks each (each of the two task trials includes 36 available stocks).

risk taking (Thaler and Johnson, 1990; Imas, 2016)–on subsequent risk aversion and risk taking.

In addition, we elicit subjects' beliefs about how many high-type stocks they selected during the investment task. This measure helps us determine whether subjects' beliefs that they selected more high-type stocks than they actually did is a possible mechanism leading to overconfidence about their investment ability.

In this setting, a price decrease is a negative signal about the selected stock's quality while a price increase is a positive signal. Across both treatments a Bayesian agent would learn from all price increases and decreases, realized or unrealized.

B. Procedure, Incentives, and Sample

The experiment was conducted online with U.S. residents of the Prolific subject pool in May 2021.[8] It was organized into two parts. The first part consisted of the investment task. In both treatments, subjects had to participate in two trials of the investment task. Their payoff depended on their choices and on the randomly generated price changes for stocks in their portfolio in one of the two task trials. In each period, subjects accumulated the proceeds from stock sales in their cash holdings and paid the cost of stocks purchased. Their potential payoff for each trial was 1/100 of their final holdings at the end of the task trial; that is, the sum of final cash holdings and the value (i.e., the current prices) of the stocks in the final portfolio after period 5. Thus payment to subjects was based on both realized and unrealized gains and losses. Part 2 of the experiment consisted of the belief elicitation, which was not incentivized. At the end of the experiment, one of the two task trials was randomly selected for payment. In addition, subjects received a fixed participation fee of $1.

We designed comprehension questions to test subjects' understanding of the experimental instructions. Subjects had to answer five comprehension questions after reading the instructions and before participating in the first part of the experiment. We excluded subjects from the experiment who gave an incorrect answer to more than one comprehension question.

A total of 301 subjects participated in the experiment, 139 subjects in treatment *Selling Gains* and 162 in treatment *Selling Losses*. Participating in the experiment took on average 12 minutes and 42 seconds. The experiment was programmed and conducted with oTree (Chen, Schonger, and Wickens, 2016). This study was pre-registered at AsPredicted under ID 66925 (https://aspredicted.org/ia5zy.pdf). Table IV reports descriptive statistics. Our sample consists of 167 female (55% of the sample) and 134 male (45% of the sample) subjects. On average, subjects were 33 years old (min. 18 years and max. 70 years). As intended,

[8] The experiment and its procedure were approved under ethical approval code ERCIC_212_28_09_2020 by the Ethical Review Committee Inner City Faculties (ERCIC) of Maastricht University. We obtained subjects' informed consent before they participated in the experiment.

subjects' number of realized gains differed significantly between our two conditions (t-test, $p = 0.000$). In the *Selling Gains* treatment, subjects realized on average 7.74 gains (out of a possible maximum of 8), whereas subjects in the *Selling Losses* treatment realized on average 0.98 gains (out of a possible maximum of 8). Subjects' profit from the investment task was similar across treatments (t-test, $p = 0.957$) and subjects selected on average a similar number of high-type stocks across treatments, namely 5.80 in the *Selling Gains* and 5.76 in the *Selling Losses* treatment (t-test, $p = 0.873$) out of 18 stocks they select in total. The average payment was $2.98, which translates to $14 per hour.

Table IV. Descriptive statistics for the experiment's subjects.

	Full sample (N = 301)			*Selling Gains* (N = 139)			*Selling Losses* (N = 162)		
	Mean	Median	St. Dev.	Mean	Median	St. Dev.	Mean	Median	St. Dev.
Female	0.55	1.00	0.50	0.53	1.00	0.50	0.58	1.00	0.50
Age (in years)	33.10	31.00	11.55	32.83	30.00	11.56	33.34	31.00	11.57
Total number of realized gains	4.10	3.00	3.48	7.74	8.00	0.50	0.98	1.00	1.03
Average portfolio performance (profit in $)	17.97	18.00	11.34	17.92	17.00	10.82	18.01	18.50	11.81
Total number of high-type stocks selected	5.78	6.00	2.12	5.80	6.00	2.11	5.76	6.00	2.13
Subject payment (in $)	2.98	2.97	0.18	2.98	2.97	0.19	2.98	2.98	0.17

C. Results

The results from our experiment provide evidence for a learning process which biases subjects' level of confidence about their ability to invest.

Result 3. *Subjects report significantly higher confidence in their own ability to invest if more gains were realized than if more losses were realized.*

The key outcome measure for our subsequent analysis is subjects' forward-looking belief about their group rank based on investment performance. Subjects reported the likelihood that they would be ranked in the upper half of a group of 10 subjects if they were to participate in another investment trial. Subjects had to provide their answer as a percentage, and every integer between 0 and 100 was admissible.

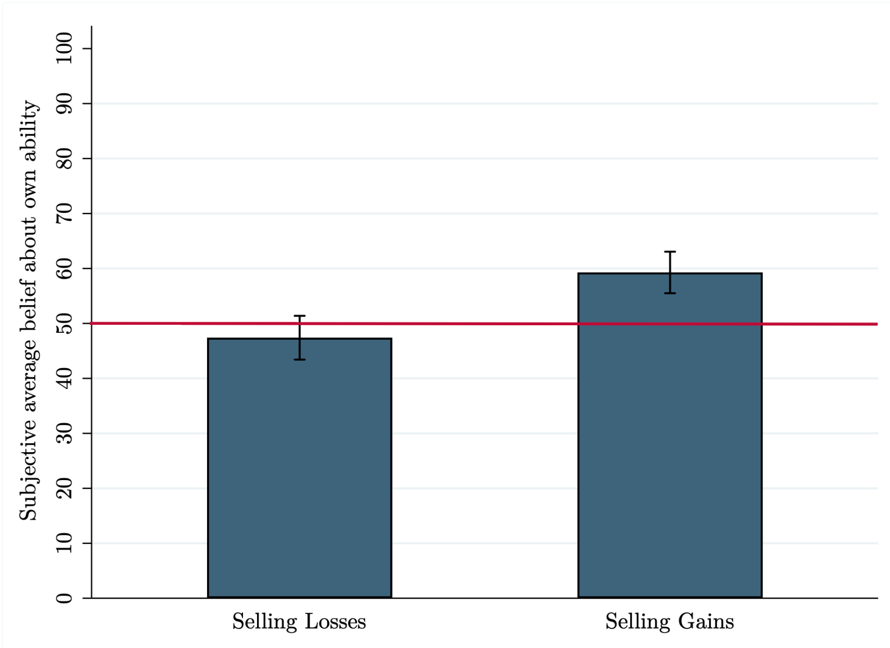

Figure 1. Average beliefs about own ability. This figure displays mean values of subjects' belief about own ability measured by subjects' elicited likelihood in percent of being ranked in the upper half of a group of 10 participants based on performance in the task (from 0% to 100%). The bars represent the mean values by treatment. Error bars indicate 95% confidence intervals. The red reference line represents the average belief if all subjects report an accurate belief about their own ability relative to others in the group (50%).

Figure 1 shows subjects' average beliefs for the two treatments. The figure confirms the basic pattern we hypothesized. On average, subjects in the *Selling Gains* treatment report significantly higher confidence in their investment ability than subjects in the *Selling Losses* treatment (t-test, $p = 0.000$). Subjects for whom mainly gains were realized, indicate a mean belief of 59.27%, whereas subjects for whom mainly losses were realized, indicate a mean belief of 47.40%.

This finding is supported in a regression analysis. Table V provides coefficients from linear estimates of subjects' beliefs. Column 1 documents the treatment effect. The coefficient of the treatment dummy is significantly positive. Subjects' average beliefs are 11.87% higher in the *Selling Gains* treatment compared to the *Selling Losses* treatment.[9]

Result 4. *Subjects form beliefs about their own ability to invest based on realized gains and losses rather than overall portfolio performance.*

We further analyze whether subjects' actual past performance in the two investment trials is related to subsequent belief reports and how it compares to our treatment effect. Subjects' past portfolio performance includes paper gains and losses and the cash position at the end of the investment trials from realized gains

[9]Note that we analyze the difference across the two exogenously varied experimental conditions, not the effect of the number of realized gains. There is only very little variation in number of realized gains within the conditions, see Table IV.

and losses. We take the average portfolio performance across both investment trials.

Column 2 of Table V provides coefficients from linear estimates of subjects' beliefs with the treatment dummy as well as their past average portfolio performance as explanatory variables. The results show that subjects in our experiment form their beliefs about own investment ability based on realized gains and losses and not based on overall portfolio performance, including paper gains and losses. The coefficient of the treatment dummy is significantly positive, however, subjects' portfolio performance with the added position of paper gains and losses has no significant association with subjects' beliefs about own ability.

Table V. Beliefs about own ability. This table contains the coefficients and robust standard errors (in parentheses) of OLS regression. The dependent variable is the subjective likelihood in percent of being ranked in the upper half of a group of 10 participants based on performance in the task (from 0% to 100%). *Treatment* is a dummy variable representing our treatment with 1 = Selling Gains and 0 = Selling Losses. *Portfolio Performance* is subjects' average portfolio performance of both investment trials, including paper gains and losses and the cash position and excluding initial endowment. *Female* is a dummy variable indicating subjects' gender with 1 = subject is female and 0 otherwise. *Individual Skill* is subjects' skill to select potential high type stocks. It indicates the number of price increases in pre-periods of selected stocks of subjects' initial portfolio in both investment trials. *Belief High Types Selected* is subjects' reported number of high-type stocks selected (from 0 to 18). *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) Belief Ability	(2) Belief Ability	(3) Belief Ability	(4) Belief Ability	(5) Belief Ability
Treatment	11.872***	11.889***	11.455***	11.384***	
	(2.79)	(2.79)	(2.78)	(2.79)	
Portfolio Performance		0.194	0.165		
		(0.13)	(0.13)		
Female			-7.836***	-7.868***	-8.463***
			(2.86)	(2.91)	(2.61)
Individual Skill				0.159	
				(0.26)	
Belief High Types Selected					2.694***
					(0.32)
Constant	47.401***	43.904***	48.981***	49.004***	37.901***
	(2.02)	(3.12)	(3.83)	(5.90)	(3.33)
N	301	301	301	301	301
R^2	0.06	0.06	0.09	0.08	0.21

Result 5. *In our sample the treatment effect on confidence is of similar magnitude to the gender effect.*

Many studies find that, while both men and women tend to exhibit overconfidence in many domains, men are generally more overconfident than women (Taylor and Brown, 1988; Lundeberg, Fox, and Punćcohaŕ, 1994), especially so in areas, such as finance and investing, that are perceived as masculine, such as finance (Deaux and Farris, 1977; Beyer and Bowden, 1997; Prince, 1993; Barber and Odean, 2001). Our experimental data is in line with this established pattern. In our sample, females' reported confidence in their ability to invest is on average 8.79 percentage points lower than males' confidence (t-test, p = 0.002). Yet, our treatment effect is robust to differences in gender. Figure 2 illustrates subjects' average beliefs for the two treatments by gender. For both genders, subjects' average belief is significantly higher in the *Selling Gains* treatment than in the *Selling Losses* treatment.

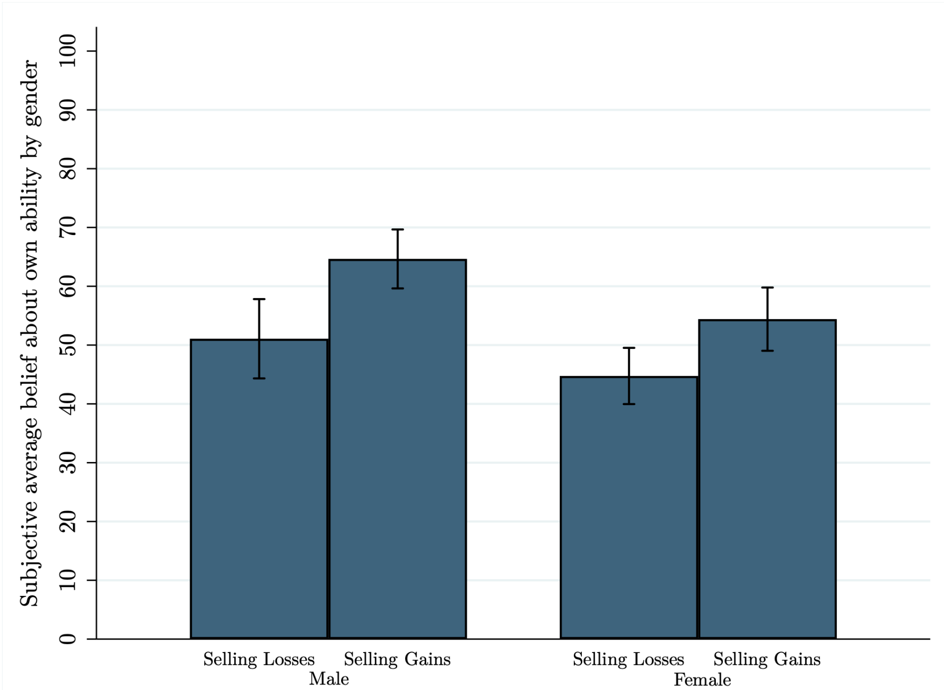

Figure 2. Average beliefs about own ability by gender. This figure displays mean values of subjects' belief about own ability measured by subjects' elicited likelihood in percent of being ranked in the upper half of a group of 10 participants based on performance in the task (from 0% to 100%). The bars represent the mean values by treatment and gender. Error bars indicate 95% confidence intervals.

In Table V, Column 3, we regress belief in ability against the treatment dummy, the portfolio performance, and a female dummy variable. The coefficient on the treatment dummy, 11.46, is hardly affected. Portfolio performance is insignificant and the female dummy variable is significant with a coefficient of -7.84. Note that the gender effect on confidence is slightly smaller, though of similar magnitude, than our treatment effect.

Subjects' portfolio performance depends on their ability to select high-type stocks as well as luck. In Column 4 of Table V, we control for subjects' individual skill to select potential high-type stocks. It reflects the normative Bayesian rule subjects should follow when selecting stocks in the experiments. It indicates the number of price increases in pre-periods of selected stocks of subjects' initial portfolio in both investment trials. This variable captures subjects' skill to select high-type stocks while ruling out any luck component. The coefficient of the treatment dummy remains significantly positive.

Result 6. *Realizing more gains leads to overconfidence.*

Besides providing evidence for a treatment effect on subjects' confidence, the experimental results document significant overconfidence in the *Selling Gains* treatment. We test for overconfidence in two ways to capture both the "better-than-average effect" as well as overplacement (Moore and Healy, 2008). In Figure 1, the red reference line represents the average belief if all subjects reported an accurate belief about their own ability relative to others in the group (50%). Yet, subjects' average belief is larger than 50% in the *Selling Gains* treatment. The figure illustrates that subjects for whom mainly gains were realized significantly overestimate their ability relative to the others, which is in line with the "better-than-average effect" (Moore and Healy, 2008). Subjects' mean belief is significantly different from and larger than 50% (t-test, $p = 0.000$).

In addition, the observed confidence patterns are related to subjects' beliefs about how many high-type stocks they have selected. In total, subjects selected 18 stocks during the two trials of the investment task. We let them report their belief about how many high-type stocks they selected during the investment task. The measure ranges from 0 to 18.

We find that subjects' confidence in own ability is positively correlated with their reports of how many high-type stocks they believe they have selected. Column 5 of Table V shows a significantly positive association between the two variables. Subjects' confidence increases by 2.7 percentage points for each additional high-type stock that they believe they have selected.

Table VI. Beliefs about number of selected high-type stocks. This table contains the coefficients and robust standard errors (in parentheses) of OLS regression. The dependent variable is subjects' reported number of high-type stocks selected (from 0 to 18). *Treatment* is a dummy variable representing our treatment with 1 = Selling Gains and 0 = Selling Losses. *Portfolio Performance* is subjects' average portfolio performance of both investment trials, including paper gains and losses and the cash position and excluding initial endowment. *Actual High Types Selected* is subjects' actual number of high-type stocks selected (from 0 to 18). *Female* is a dummy variable indicating subjects' gender with 1 = subject is female and 0 otherwise. *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) Belief High Types Selected	(2) Belief High Types Selected	(3) Belief High Types Selected	(4) Belief High Types Selected
Treatment	0.956**	0.958**	0.957**	0.956**
	(0.45)	(0.45)	(0.45)	(0.45)
Portfolio Performance		0.029	0.027	0.027
		(0.02)	(0.02)	(0.02)
Actual High Types Selected			0.037	0.036
			(0.11)	(0.11)
Female				-0.008
				(0.46)
Constant	6.864***	6.348***	6.167***	6.173***
	(0.31)	(0.48)	(0.74)	(0.81)
N	301	301	301	301
R^2	0.01	0.02	0.02	0.02

We investigate whether our treatment leads people to believe that they have selected more or less high-type stocks. Table VI provides coefficients from linear estimates of subjects' report of how many high-type stocks they believe they have selected during the investment task. We find that subjects believe that they have selected significantly more high-type stocks if more gains were realized than if more losses were realized. The coefficient of the treatment dummy in Column 1 is significantly positive. Subjects for whom mainly gains were realized believe they have selected on average 7.82 high-type stocks, whereas subjects for whom mainly losses were realized believe they have selected on average 6.86 high-type stocks. Note that, as reported in Table IV, subjects in both treatment groups selected an average of 5.8 (median of 6) high type stocks. Thus subjects believe they have selected more high-type stocks than they actually did which is in line with overplacement (Moore and Healy, 2008).

Column 2 of Table VI provides coefficients from linear estimates of subjects' beliefs with the treatment dummy as well as their past average portfolio performance as explanatory variables. Similar to subjects' confidence, we find that subjects form beliefs about how many high-type stocks they have selected based on realized gains and losses rather than overall portfolio performance. The coefficient of the treatment dummy is significantly positive, however, subjects' portfolio performance has no significant association with subjects' beliefs about selected high-type stocks selected. This result holds when we control for the actual number of high type stocks the subjects selected (column 3) and gender (column 4).

IV. The Model

In this section, we present a simple model demonstrating how the biased learning process leads to overconfidence. The model has two assumptions. First, investors assess their trading ability (which will be defined precisely later) by counting past realized gains and losses. Second, investors are subject to biased realizations in their selling decisions. We study the implications of such a model. We organize the model's implications by three parts: the implications for investor confidence; the implications for trading behavior; and the implications for the investor's expected profit.

A. Model Setup

Asset space—We consider a finite-horizon economy with N risky assets which we also refer to as stocks. Each asset has a liquidating dividend paid at the end of period T; denote the liquidating dividend for asset i as $D_{i,T}$. News about $D_{i,T}$ is sequentially released over time. The incremental news released at the end of period t about $D_{i,T}$ is denoted as $v_{i,t}$ and the cumulative news released by the end of period t about $D_{i,T}$

is denoted as $D_{i,t}$. We have

$$D_{i,t} = D_{i,0} + v_{i,1} + v_{i,2} + \cdots + v_{i,t}, \quad 1 \leq i \leq N \text{ and } 1 \leq t \leq T. \tag{3}$$

We further assume

$$\begin{gathered} v_{i,t} \sim \mathcal{N}(0, \sigma_i^2), \quad t \geq 1, \ \forall i, \\ \text{i.i.d. over time and independent across stocks.} \end{gathered} \tag{4}$$

Signal structure—At the beginning of period t, a risky asset—asset i, say—is randomly selected from N risky assets. One type of market participant, a risk-neutral investor, is endowed with the following signal about asset i

$$\theta_{i,t} = \delta_{i,t} v_{i,t} + (1 - \delta_{i,t})\varepsilon_{i,t}, \tag{5}$$

where $\varepsilon_{i,t}$ has an identical distribution as $v_{i,t}$ but is independent from it. The variable $\delta_{i,t}$ takes the values of one or zero: when $\delta_{i,t} = 1$ the signal is $\theta_{i,t} = v_{i,t}$, hence it is fully informative about the quality of the asset; when $\delta_{i,t} = 0$, the signal is $\theta_{i,t} = \varepsilon_{i,t}$ and the signal is pure noise. Therefore, it makes sense to posit that the investor's ability for correctly anticipating the payoff of asset i is measured by the *probability* that $\delta_{i,t}$ takes the value of one. Denote this probability as a_i and refer to it as the investor's ability. We assume that there are two possible ability levels: $a_i = H$ and $a_i = L$, where $0 < L < H < 1$.

We assume that no market participant, including the investor, knows the investor's ability. Instead, all market participants are endowed with the correct prior belief that $a_i = H$ with probability ϕ_0 and $a_i = L$ with probability $1 - \phi_0$, where $0 < \phi_0 < 1$. Moreover, we assume that the investor's ability for correctly anticipating the payoff of asset i also represents his ability for correctly anticipating the payoff of another asset; that is, ability is at the investor level, not at the asset level (formally, $a_i = a_j$ for all $i, j \leq N$). As such, we abbreviate a_i as a. Finally, we assume $N \gg T$, so the probability that the investor obtains a signal for the same asset over two different time periods is negligible (recall that the signal is about a risky asset chosen at random).

Market participants—There are three market participants: the investor mentioned above, a liquidity trader, and a market maker. We discuss them in order.

The investor starts with rational prior beliefs about his ability, but he develops biased beliefs over time, due to a misspecified updating rule. We first describe the rational beliefs about the investor's ability. We then discuss how the investor's beliefs differ from the rational beliefs. As in Gervais and Odean (2001), let s_t denote the number of times that the investor's information about risky assets was true by the end of the first t periods: we write $s_t = \sum_{u=1}^{t} \delta_{i(u),u}$, where $i(u)$ denotes the asset about which the investor has a signal in period u; $\delta_{i(u),u}$ equals one if $\theta_{i(u),u} = v_{i(u),u}$, and $\delta_{i(u),u}$ equals zero if $\theta_{i(u),u} \neq v_{i(u),u}$. Under rational beliefs, the investor would correctly understand that the number of times his information was true in the past is diagnostic of his ability. Hence, at the beginning of period t, after his information was true $s_{t-1} = s$ times, a rational investor would update beliefs about his ability according to Bayes' rule,

$$\begin{aligned}\phi_{t-1}(s) \equiv \Pr(a = H|s_{t-1} = s) = &\frac{\Pr(a = H)\Pr(s_{t-1} = s|a = H)}{\Pr(a = H)\Pr(s_{t-1} = s|a = H) + \Pr(a = L)\Pr(s_{t-1} = s|a = L)} = \\ = &\frac{H^s(1-H)^{t-1-s}\phi_0}{H^s(1-H)^{t-1-s}\phi_0 + L^s(1-L)^{t-1-s}(1-\phi_0)}.\end{aligned} \tag{6}$$

To understand the formula, recall that $\Pr(s_{t-1} = s|a = A) = A^s(1-A)^{t-1-s}$ for $A \in \{H, L\}$, since $(\delta_{i,u})_{u=1}^{t}$ is a vector of i.i.d Bernoulli random variables for which $\Pr(\delta_{i,u} = 1|a = A) = A$.

Therefore, the rational expectation about the investor's ability, computed at the beginning of period t, is

$$\xi_{t-1}(s) \equiv \mathbb{E}(a|s_{t-1} = s) = \phi_{t-1}(s) \cdot H + (1 - \phi_{t-1}(s)) \cdot L. \tag{7}$$

And, since a is the probability that $\delta = 1$, $\xi_{t-1}(s)$ is the rational investor's expectation that his period t information is true, after it has been true s times over the last $t-1$ observations.

In our model, the investor deviates from rational beliefs as follows. To assess his ability, rather than using s_t, the investor uses the number of times that he has sold stocks for a gain, denoted by k_t. Gains and losses for an asset i at time t are defined as the difference between the asset's price at time $t-1$ and its purchase price in the case of positive share demand; vice versa for negative share demand. Later we will provide a precise definition of stock-level gains and losses.

Under the investor's biased beliefs, the probability that $a = H$ at the beginning of period t, is

$$\psi_{t-1}(k) \equiv \Pr_b(a = H|k_{t-1} = k) := \frac{H^k(1-H)^{t-1-k}\phi_0}{H^k(1-H)^{t-1-k}\phi_0 + L^k(1-L)^{t-1-k}(1-\phi_0)}, \tag{8}$$

where the subscript "b" denotes biased beliefs.

Accordingly, the investor's biased expectation of his ability, computed at the beginning of period t, is

$$\Xi_{t-1}(k) \equiv \mathbb{E}_b(a|k_{t-1} = k) = \psi_{t-1}(k) \cdot H + (1 - \psi_{t-1}(k)) \cdot L. \tag{9}$$

And, since a is the probability that $\delta = 1$, $\Xi_{t-1}(s)$ is the biased investor's expectation that his information is true, after he has sold for a gain k times over the last $t-1$ periods.

We now turn to the investor's buying and selling decisions. Selling decisions follow an exogenous rule. At any time $t < T$, the investor holds $M \ll N$ risky assets in his portfolio. Suppose that M_1 out of M stocks are held at a gain, and that the remaining $M - M_1$ stocks are held at a loss, where gains and losses are defined as below. With probability χ, the investor will randomly sell one of the M_1 stocks, resulting in a gain realization; with the remaining probability $1 - \chi$, the investor will randomly sell one of the $M - M_1$ stocks resulting in a loss realization.[10] At time T, the investor sells all his stocks. The probability χ measures the intensity of the bias to sell rather for a gain than a loss (i.e., a disposition effect), to which the investor is subject. For example, for values of χ close to 1, the investor will almost surely sell an asset held at a gain and keep assets held at a loss.

At the beginning of period $t < T$, once the investor sells a stock, he receives a signal $\theta_{i,t}$ about a new asset i according to the signal structure described above. Given this signal and the investor's biased belief about his ability (which is based on k_{t-1}), the investor maximizes the expected profit of holding asset i by choosing $x_{i,t}$, his share demand for asset i. We further describe this maximization problem in the next section. Note that, though assets in the investor's portfolio may be held for multiple periods, the investor only receives a signal about an asset when he makes the initial purchase decision. At the end of each period, the price of the asset is set to its fair value, $D_{i,t}$.

The liquidity trader has a random demand for the asset that the investor buys; denote this demand at the beginning of period t as $z_{i,t}$. We suppose that $z_{i,t}$ is a Normal random variable: $z_{i,t} \sim \mathcal{N}(0, \sigma^2_{i,z})$, independent from all other variables.

As in Kyle (1985), we assume that the market maker is risk-neutral and competitive and will therefore set prices so as to make zero expected profits. Furthermore, the market maker holds rational beliefs. At the beginning of period t, he observes s_{t-1}, k_{t-1}, and $\omega_{i,t} = x_{i,t} + z_{i,t}$, which is the total demand from the investor and the liquidity trader for asset i. The market maker then sets a competitive price $p_{i,t}$ for asset i. In other words, he sets a price equal to his expectation $\mathbb{E}[D_{i,T}]$ at the beginning of period t. Note that, at the beginning of period t, the market maker does not observe $\theta_{i,t}$ or $v_{i,t}$.

B. *Model Implications*

We formally solve the model in Appendix E. With the model's solution in hand, we now examine the model's implications through numerical simulations. We examine the implications for investor confidence, trading behavior, and expected profits.

Specifically, we set $M = 10$, $T = 10$, $L = 0.4$, $H = 0.6$, $\sigma_i = 1$, $\sigma_{i,z} = 1$, and $\phi_0 = 0.5$. With $T = 0$, the economy has eleven dates (date t goes from zero to ten) and ten periods. At date 0, the investor's ability

[10] If M_1 equals zero or M, then the investor randomly sells one out of all M stocks.

level is drawn: with probability ϕ_0, $a = H$; and with probability $1-\phi_0$, $a = L$. The investor is then endowed with ten stocks. At each date $1 \leq t \leq 9$, the investor sells one of the ten stocks according to the probability χ described in the previous section; he is endowed with a signal about a new stock; and he decides his share demand for the stock. At date $t = 10$, the investor sells all his stocks.

Investor overconfidence.—We record the investor's overconfidence level at date $t = 9$ (the beginning of the final period, period 10), measured by $\Xi(k) - \xi(s)$. Thus, overconfidence on our model captures how much an investor overplaces his perceived ability to his true ability (Moore and Healy, 2008). We simulate the above economy for 10,000 times. We compute the level of overconfidence averaged across the 10,000 investors and then plot it against probability χ. Figure 7 below presents this result in Panel a).

The graph in Panel a) shows that investor overconfidence increases with χ. Moreover, when χ is low, $\xi(s)$ tends to be greater than $\Xi(k)$ and hence investors exhibit underconfidence. When χ is high, $\xi(s)$ tends to be lower than $\Xi(k)$ and hence investors exhibit overconfidence.

We further look at investor overconfidence separately for the low-type investors and the high-type investors. We find that, for all values of χ, the low-type investors tend to be more overconfident than the high-type investors. In particular, when χ is high, the rational expectation about the low-type investors' ability, computed at date $t = 9$, is close to $L = 0.4$. However, the low-type investors' subjective expectation about their ability, after these investors have experienced many gain realizations by date $t = 9$, is significantly higher than 0.4.

Next, we examine how investor overconfidence varies over time. For this exercise, we set $T = 21$ so the economy has 22 dates (date t goes from zero to 21) and 21 periods. We set $\chi = 1$, so investors always sell stocks at a gain (so long as there is at least one stock in the portfolio that is held at a gain). Panel b) of Figure 7 plots, for $1 \leq t \leq 20$, the level of overconfidence averaged across all investors, across the high-type investors, and across the low-type investors. Overall, the level of investor overconfidence increases over time: the increase is particularly significant for the first few periods and then becomes smaller and eventually negligible.

The dynamics of investor overconfidence depend strongly on the investor's type. Low-type investors tend to become more overconfident over time: their subjective expectation about their ability increases as they experience a higher number of gain realizations, while the rational expectation about their ability decreases over time towards their true ability $a = L$. High-type investors, however, tend to become more overconfident only for the first few periods; subsequently, their level of overconfidence decreases towards zero. For these investors, their subjective expectation about their trading ability initially increases at a faster pace compared to the rational expectation, leading to a higher level of overconfidence. As time goes, both the subjective expectation and the rational expectation converges to the investors' true ability $a = H$, and therefore the

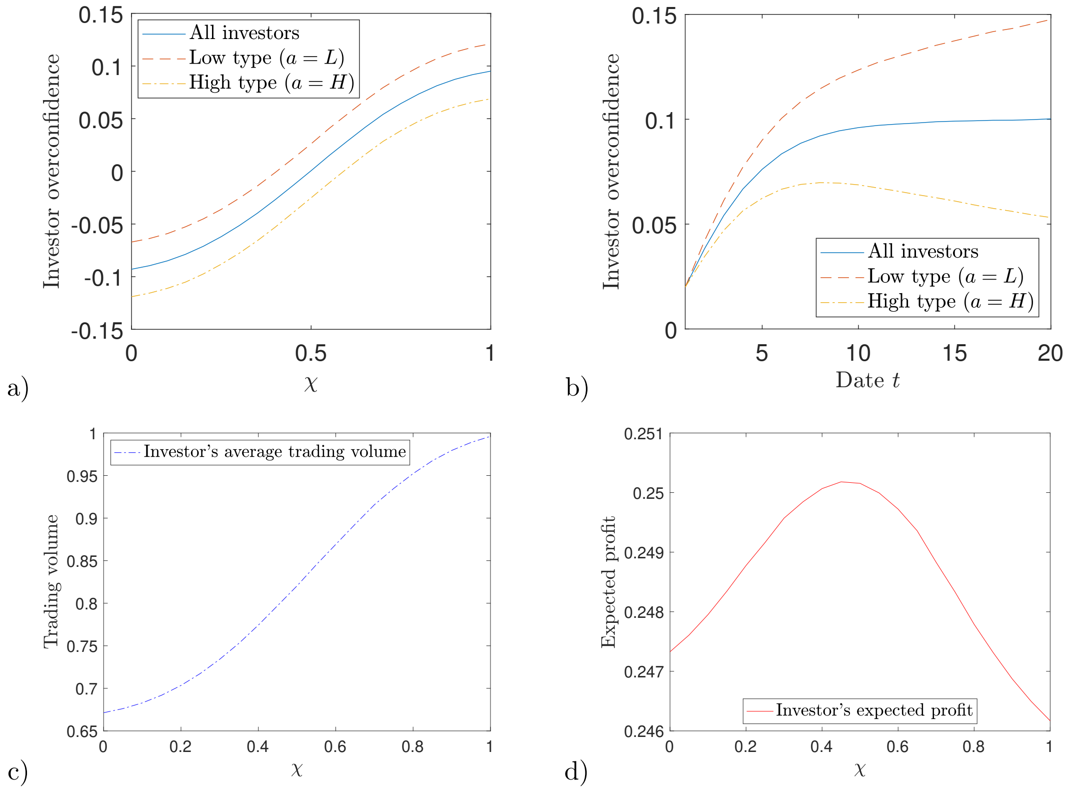

Figure 7. Model implications. We simulate the economy 10,000 times for T periods. At date 0, we draw the investor's ability level. For all panels, $M = 10$, $L = 0.4$, $H = 0.6$, $\sigma_i = 1$, $\sigma_{i,z} = 1$, and $\phi_0 = 0.5$. For Panels a, c, and d, T = 10. For Panel b, T = 21. For Panel b, $\chi = 1$.
Panel a): The graph plots investor overconfidence as a function of χ. We record the investor's overconfidence level at the beginning of the final period, measured by $\Xi(k) - \xi(s)$. We then compute the average level of investor overconfidence for all 10,000 investors, for low type investors, and for high type investors.
Panel b): The graph plots investor overconfidence as a function of time averaged across all 10,000 investors. We record the investor's overconfidence level at the beginning of each period, measured by $\Xi(k) - \xi(s)$.
Panel c): The graph plots the investor's average trading volume as a function of χ for all 10,000 investors. We record the investor's absolute share demand for a risky asset at the beginning of the final period measured by $|x|$.
Panel d): The graph plots the investor's expected profit from the final investment as a function of χ for all 10,000 investors. We record the objective expectation of the investor's profit from the final investment made at the beginning of the final period.

level of overconfidence drops.

Trading behavior—We set $T = 10$ and simulate the economy for 10,000 times. For each simulation, we compute the magnitude of the investor's share demand for the new risky asset at the beginning of the final period (period 10), measured by $|x|$, where x is the share demand from equation (E.5). We then compute the absolute share demand, $|x|$, averaged across the 10,000 investors and plot the share demand against probability χ. Panel c) of Figure 7 presents this result. The graph shows that the magnitude of the investor's share demand for risky assets increases with χ, the tendency to sell rather for a gain than a loss.

For high values of χ, the learning mechanism gives rise to investor overconfidence. This, in turn, generates excessive trading ($|x| > |x^R|$).

Expected profit.—At the beginning of the final period, the expectation of the investor's profit from the final investment is

$$\begin{aligned} \mathbb{E}[\pi_{i,t}|\theta_{i,t}, s_{t-1}, k_{t-1}, x_{i,t}] &= x_{i,t} \cdot [\mathbb{E}[v_{i,t}|\theta_{i,t}, s_{t-1}] - \lambda_{i,t}(s_{t-1}, k_{t-1}) \cdot x_{i,t}] \\ &= x_{i,t} \cdot [\xi_{t-1}(s_{t-1}) \cdot \theta_{i,t} - \lambda_{i,t}(s_{t-1}, k_{t-1}) \cdot x_{i,t}] \,. \end{aligned} \tag{10}$$

Panel d) of Figure 7 plots the expectation of the investor's profit against probability χ. The graph in Panel d) shows that the investor's expected profit is hump shaped in χ. For low values of χ, the investor's demand is too low to maximize profits and when χ the investor's demand is too high to maximize profits. In our model, the investor is the only market participant with a signal about the future value of a risky asset. Thus the investor's expected profits are positive. High values of χ lead to investor overconfidence, which in turn gives rise to excessive trading. In the model, excessive trading is detrimental to the investor's gross profit because such trading reveals too much information to the market maker. In actual markets, excessive trading further reduces net profit because retail investors incur transaction costs (Barber and Odean, 2000).

V. Conclusion

We document that when learning about their own investment ability investors use a metric based on realizations. This metric is appealing, since it is cognitively tractable, uses information that easily comes to mind, and is similar to metrics used in other domains of life. Yet it is biased by investors' tendency to sell gains more readily than losses relative to opportunities, i.e., the disposition effect, and by the tendency to remember realizing more gains than one actually realized. In conjunction with these biases, the learning mechanism generates investor overconfidence.

In field data we find that Dutch retail investors who realized more gains than losses report higher confidence in ability relative to other retail investors, controlling for actual portfolio performance. Furthermore, retail investors selectively recall their realized gains and losses. They recall a higher number of gains than actually realized, but do not significantly misremember losses. Selective recall is associated with an even more optimistic belief about own ability.

In an experiment, we document the causal effect of gain/loss realizations on individuals' confidence. Subjects randomly assigned to a treatment in which gains are sold more readily than losses, become overconfident in their abilities, while those in a treatment in which losses are sold more readily than gains do not. Controlling for actual performance on the investment task, subjects in our *Selling Gains* condition, who realized mainly gains during the task, are more confident in their ability to select high-type stocks than subjects in the *Selling Losses* condition. Subjects in the *Selling Gains* believe that they selected significantly more high-type stocks than they actually did and overestimate their ability to perform well on a future investment task relative to others. Many studies find that men are generally more overconfident than women. We replicate this empirical pattern, but find that both men and women form their beliefs about own ability based on realized gains and losses rather than overall portfolio performance. In our sample, the treatment effect on confidence is of similar magnitude to the gender effect.

Building on our empirical results, we develop a theoretical model of how the disposition effect as well as self-serving memory bias can lead to overconfidence, excessive trading, and lower trading profits. In our model, investors assess their trading ability by counting past realized gains and losses. Investors who realize more gains because of the disposition effect or, equivalently, remember realizing more gains because of memory bias, are disposed to be overconfident.

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Appendices

A. Experimental Instructions

Instructions of Investment Task

In the investment task, you select **stocks**. Each period a stock can either increase or decrease in price.

There are two types of stock: an ordinary type and a high type. **These two stock types differ in the probability that their price increases or decreases**. An ordinary-type stock has a 40% probability of a price increase and a 60% probability of a price decrease. A high-type stock has a 60% probability of a price increase and a 40% probability of a price decrease.

If the price increases, the price change is **+ $2 or + $6, with equal probability**.
If the price decreases, the price change is **- $1 or - $3, with equal probability**.

The purchase price of a stock is always $30.

NEXT SCREEN

The investment task consists of 5 periods. Each period, a stock's price either increases or decreases.

First investment choice
You begin the investment task with $180 and must buy a portfolio of 5 stocks from a list of 20 available stocks. Each stock is priced at $30.

The list contains exactly 15 ordinary-type stocks and exactly 5 high-type stocks. You are not told which stock is of which type. However, for each of the 20 stocks, you are shown price changes from the three previous periods.

The picture below shows you how your choice screen will look like. You will be asked to choose 5 stocks of such a list.

Stock	3 periods ago	2 periods ago	1 period ago	Current price	Your choice
Stock 1	$ 23	$ 22	$ 28	$ 30	☐
Stock 2	$ 32	$ 31	$ 28	$ 30	☐
Stock 3	$ 28	$ 34	$ 31	$ 30	☐
Stock 4	$ 26	$ 25	$ 31	$ 30	☐
Stock 5	$ 28	$ 27	$ 24	$ 30	☐
Stock 6	$ 37	$ 36	$ 33	$ 30	☐
Stock 7	$ 34	$ 31	$ 33	$ 30	☐
Stock 8	$ 16	$ 22	$ 24	$ 30	☐
Stock 9	$ 37	$ 36	$ 33	$ 30	☐
Stock 10	$ 33	$ 32	$ 31	$ 30	☐
Stock 11	$ 34	$ 36	$ 33	$ 30	☐
Stock 12	$ 34	$ 31	$ 33	$ 30	☐
Stock 13	$ 32	$ 29	$ 28	$ 30	☐
Stock 14	$ 37	$ 34	$ 33	$ 30	☐
Stock 15	$ 33	$ 32	$ 31	$ 30	☐
Stock 16	$ 33	$ 32	$ 31	$ 30	☐
Stock 17	$ 26	$ 25	$ 31	$ 30	☐
Stock 18	$ 34	$ 36	$ 33	$ 30	☐
Stock 19	$ 34	$ 31	$ 28	$ 30	☐
Stock 20	$ 33	$ 32	$ 31	$ 30	☐

Example Screen.

NEXT SCREEN

First period

After the initial portfolio selection, you observe the first period price changes for each of the stocks in your portfolio. After the new prices are displayed, **one of the stocks is automatically sold** by the computer program at the stock's current price. After the sale of one stock, you **must buy an additional stock from a new list of four stocks**. Once again, you observe the previous three price changes for each of the four stocks. The purchase price of each stock is always $30.

The list contains exactly 3 ordinary-type stocks and exactly 1 high-type stock. You are not told which stock is of which type. However, for each of the 4 stocks, you are shown price changes from the three previous periods.

Periods 2-4

You observe the next period's new prices for each of the stocks in your portfolio. After the new prices are displayed, **one of the stocks is automatically sold** by the computer program at the stock's current price. After the sale of one stock, you **must buy an additional stock from a new list of four stocks**. Once again, you observe the previous three price changes for each of the four stocks. The purchase price of each stock is always $30.

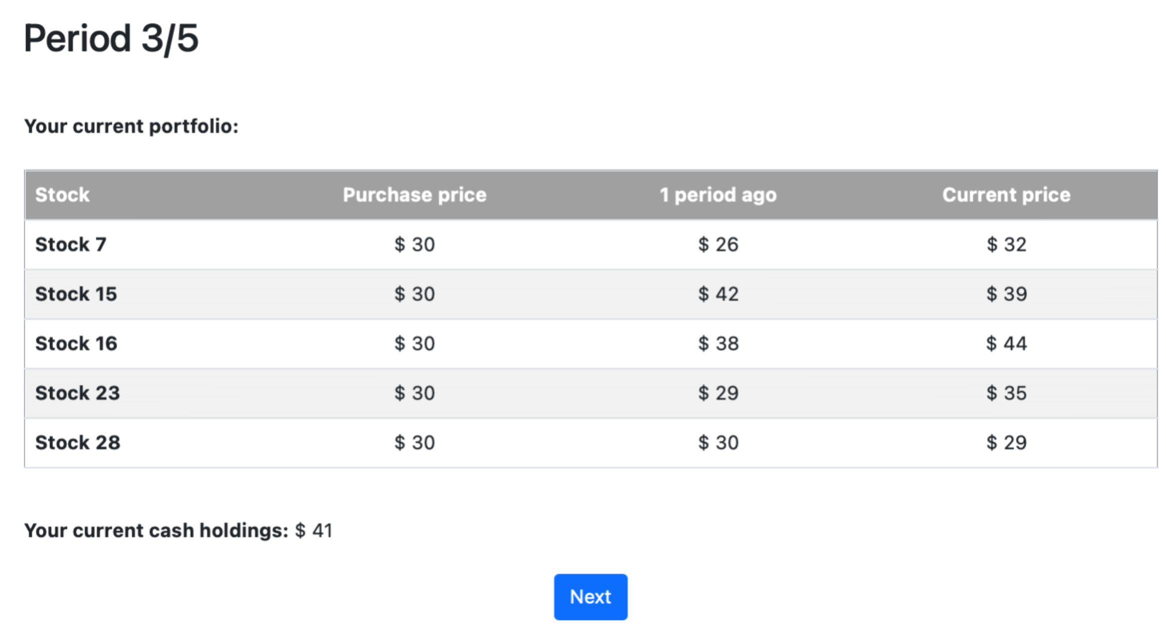
As in period 1, the list contains exactly 3 ordinary-type stocks and exactly 1 high-type stock. You are not told which stock is of which type. However, for each of the 4 stocks, you are shown price changes from the three previous periods.

Period 5

You observe the new prices for each of the stocks in your portfolio. The investment task is now over.

B. Example Screen

In each period, subjects observed the purchase price, the price from one period ago, and the current price of all stock positions in the portfolio.



Period 3/5

Your current portfolio:

Stock	Purchase price	1 period ago	Current price
Stock 7	$ 30	$ 26	$ 32
Stock 15	$ 30	$ 42	$ 39
Stock 16	$ 30	$ 38	$ 44
Stock 23	$ 30	$ 29	$ 35
Stock 28	$ 30	$ 30	$ 29

Your current cash holdings: $ 41

Next

Example Screen: Overview of portfolio positions.

C. Explanations for the Disposition Effect

Shefrin and Statman (1985) coin the term "Disposition Effect" and attribute the behavior to a combination of Prospect Theory; mental accounting; regret aversion; and self-control. They discuss the emotions of regret and pride pointing out that "While closing a stock account at a loss induces regret, closing at a gain induces pride." Weber and Camerer (1998) find the disposition effect in an experimental setting and Odean (1998a) finds it for individual investors.

Odean (1998a) considers and rejects several potential explanations for the disposition effect including rebalancing, transactions costs, and superior information. The author notes that the disposition effect could be driven by a belief that stock prices mean revert but that retail investors tend to buy stocks that have been going up, which is inconsistent with a belief in mean reversion. One exception to this tendency is that investors are more likely to buy additional shares of a stock that they already own if it has gone down since they bought it (which is consistent with a belief in mean reversion). Odean (1998a) also points out that reference points are likely to be path dependent and not simply equal to purchase price.

Several subsequent papers argue that the disposition effect cannot be explained by Prospect Theory (Barberis and Xiong, 2009; Kaustia, 2010b; Hens and Vlcek, 2011; Meng and Weng, 2018). Barberis and Xiong (2012) generate a disposition effect in a theoretical setting by assuming that investors derive utility from the act of selling for a gain (realization utility). Frydman et al. (2014) find neurological activity consistent with realization utility in an investment like setting.

Seru, Shumway, and Stoffman (2010) document that, controlling for time held, the propensity to sell is V-shaped in a stock's return since purchase.

Ben-David and Hirshleifer (2012) point out that realization utility fails to account for this V-shaped selling pattern or for the propensity to purchase additional shares of a stock already owned at prices below the purchase price. Ben-David and Hirshleifer (2012) propose that the disposition effect, and related trading behaviors, can be explained by overconfident beliefs.

Finally, several papers argue that the investors' selling and repurchase decisions are the result of investors choosing behaviors that avoid or postpone the negative emotion of regret (Muermann and Volkman Wise, 2006; Summers and Duxbury, 2012; Strahilevitz et al., 2011; Weber and Welfens, 2011).

See Kaustia (2010a) and Barber and Odean (2013) for more detailed discussions of this literature.

D. Robustness

Table AI. Beliefs about own performance of Dutch retail investors. This table shows the results of Table II, restricting the sample to investors who at least had 2 realizations in 2019. The table contains the coefficients and robust standard errors (in parentheses) of OLS regressions. The dependent variable is the investors' beliefs about their performance-based rank among other retail investors, *Elicited Percentile Rank*, (between 0 and 100). *Net Gains* is the difference in the number of investors' realized gains and losses in 2019. *Recalled Net Gains* is the difference in the recalled number of investors' realized gains and losses in 2019. *Actual Percentile Rank* is investors' actual percentile rank among all retail clients at the financial institution based on annual portfolio performance in 2019 (from 0 to 100). *Order of Elicitation* is a dummy variable indicating the order in which our two survey items were elicited (1 = recall of realizations first and 0 = otherwise). *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) Elicited Perc. Rank	(2) Elicited Perc. Rank	(3) Elicited Perc. Rank	(4) Elicited Perc. Rank
Net Gains	0.476***	0.345**		
	(0.15)	(0.15)		
Recalled Net Gains			0.613***	0.537***
			(0.17)	(0.17)
Actual Perc. Rank		0.171***		0.121***
		(0.02)		(0.04)
Order of Elicitation				-1.474
				(2.24)
Constant	55.420***	46.176***	56.653***	52.033***
	(0.66)	(1.31)	(1.33)	(4.33)
N	1,320	1,320	348	348
R^2	0.01	0.06	0.03	0.06

E. Solution to Model

We now describe the procedure for solving the model. We conjecture that, at the beginning of period t, the equilibrium for asset i that is being traded has the following linear structure:

$$\begin{aligned} p_{i,t}(\omega_{i,t}, s_{t-1}, k_{t-1}) &= D_{i,t-1} + \lambda_{i,t}(s_{t-1}, k_{t-1}) \cdot \omega_{i,t}, \\ x_{i,t}(\theta_{i,t}, s_{t-1}, k_{t-1}) &= \beta_{i,t}(s_{t-1}, k_{t-1}) \cdot \theta_{i,t}, \end{aligned} \tag{E.1}$$

where $p_{i,t}$ is the price for asset i, $x_{i,t}$ is the investor's demand for asset i, $\omega_{i,t} = x_{i,t} + z_{i,t}$ is the total demand from the investor and the liquidity trader, s_{t-1} is the number of times investor's information was true in the past, and k_{t-1} is the number of times the investor sold an asset for a gain.

We first solve the investor's problem, taking the conjectured equilibrium price rule as given. The investor is risk neutral and chooses the demand, $x_{i,t}$, that maximizes his biased expectation of the profits he will make on asset i, given his information $(\theta_{i,t}, k_{t-1})$.[11] Under the conjectured equilibrium structure, the investor anticipates that profits when demanding share $x_{i,t}$ of asset i will be

$$\pi_{i,t} \equiv x_{i,t} \cdot (D_{i,t} - p_{i,t}) = x_{i,t} \cdot (D_{i,t} - D_{i,t-1} - \lambda_{i,t}(s_{t-1}, k_{t-1})\omega_{i,t} = x_{i,t} \cdot (v_{i,t} - \lambda_{i,t}(s_{t-1}, k_{t-1})(x_{i,t} + z_{i,t})) \tag{E.2}$$

where we used the fact that $v_{i,t} = D_{i,t} - D_{i,t-1}$ and $\omega_{i,t} = x_{i,t} + z_{i,t}$. The investor's objective is to maximize

$$\begin{aligned} \mathbb{E}_b[\pi_{i,t}|\theta_{i,t}, k_{t-1}] &= \mathbb{E}_b\left[x_{i,t} \cdot (v_{i,t} - \lambda_{i,t}(s_{t-1}, k_{t-1})(x_{i,t} + z_{i,t}))|\theta_{i,t}, k_{t-1}\right] \\ &= -x_{i,t}^2 \lambda(s_{t-1}, k_{t-1}) + x_{i,t}[\mathbb{E}_b[v_{i,t}|\theta_{i,t}, k_{t-1}] + \lambda(s_{t-1}, k_{t-1}) \underbrace{\mathbb{E}_b[z_{i,t}|\theta_{i,t}, k_{t-1}]}_{=0}]. \end{aligned} \tag{E.3}$$

Note that the expectation is linear, that $z_{i,t}$ is independent from a, and that the investor has correct expectations about $z_{i,t}$, therefore $\mathbb{E}_b[z_{i,t}|\theta_{i,t}, k_{t-1}] = \mathbb{E}[z_{i,t}] = 0$. To find $x_{i,t}$ that maximizes $\mathbb{E}_b[\pi_{i,t}|\theta_{i,t}, k_{t-1}]$, we set the first order derivative equal to 0

$$\mathbb{E}_b[v_{i,t}|\theta_{i,t}, k_{t-1}] - 2\lambda_{i,t}(s_{t-1}, k_{t-1})x_{i,t} = 0 \tag{E.4}$$

and solve for $x_{i,t}$

$$x_{i,t}(\theta_{i,t}, s_{t-1}, k_{t-1}) = \frac{\mathbb{E}_b[v_{i,t}|\theta_{i,t}, k_{t-1}]}{2\lambda_{i,t}(s_{t-1}, k_{t-1})} = \frac{\Xi_{t-1}(k_{t-1})}{2\lambda_{i,t}(s_{t-1}, k_{t-1})} \cdot \theta_{i,t} \tag{E.5}$$

Note that $\Pr_b(\delta_{i,t} = 1|\theta_{i,t}, k_{t-1}) = \Xi(k_{t-1})$ and $\mathbb{E}_b[v_{i,t}|\theta_{i,t}, k_{t-1}, \delta_{i,t} = 0] = \mathbb{E}[v_{i,t}] = 0$. Therefore, by the

[11] The investor also observes s_{t-1}, but deems this quantity irrelevant in updating his beliefs

law of iterated expectations,[12]

$$\mathbb{E}_b[v_{i,t}|\theta_{i,t},k_{t-1}] = \mathbb{E}_b[v_{i,t}|\theta_{i,t},k_{t-1},\delta_{i,t}=1]\Pr_b(\delta_{i,t}=1|\theta_{i,t},k_{t-1})+\mathbb{E}_b[v_{i,t}|\theta_{i,t},k_{t-1},\delta_{i,t}=0]\Pr_b(\delta_{i,t}=0|\theta_{i,t},k_{t-1}) \tag{E.6}$$

Next we solve the market maker's problem which is to set the fair price for asset i at the beginning of period t, i.e., the market maker imposes a price equal to his unbiased expectation of $D_{i,t}$ at the beginning of period t. We assume that the investor chooses his demand as conjectured in Equations (E.1) and that the market maker solves for:

$$p_{i,t} = \mathbb{E}[D_{i,t}|\omega_{i,t},s_{t-1},k_{t-1}]$$

Recalling that $D_{i,t} = D_{i,t-1} + v_t$ we have

$$p_{i,t} = D_{i,t-1} + \mathbb{E}[v_t|\omega_{i,t},s_{t-1},k_{t-1}]$$

As before, we can use the law of iterated expectations to evaluate the second quantity. Begin with:

$$\mathbb{E}[v_t|\omega_{i,t},s_{t-1},k_{t-1}] = \mathbb{E}[v_t|\omega_{i,t},s_{t-1},k_{t-1},\delta_{i,t}=1]\Pr(\delta_{i,t}=1) + \mathbb{E}[v_t|\omega_{i,t},s_{t-1},k_{t-1},\delta_{i,t}=0]\Pr(\delta_{i,t}=0) \tag{E.7}$$

Now recall that, under our conjecture of the equilibrium structure, $x_{i,t} = \beta_{i,t}(s_{t-1},k_{t-1})\cdot\theta_{i,t}$. As a consequence, the market maker anticipates $\omega_{i,t} = \beta_{i,t}(s_{t-1},k_{t-1})\cdot\theta_{i,t} + z_{i,t}$. Then, conditional on $\delta_{i,t}=1$, we have $v_{i,t} = \theta_{i,t}$ and, in this case, the vector $(v_{i,t},\omega_{i,t})$ is the vector $(v_{i,t},\beta_{i,t}(s_{t-1},k_{t-1})\cdot v_{i,t} + z_{i,t})$ which is jointly normal with mean vector and variance-covariance matrix

$$\mu = (0,0) \qquad \Sigma = \begin{bmatrix} \sigma_i^2 & \beta_{i,t}^2\sigma_i^2 \\ \beta_{i,t}^2\sigma_i^2 & \beta_{i,t}^2\sigma_i^2 + \sigma_{i,z}^2 \end{bmatrix}. \tag{E.8}$$

These are easily computed recalling that $v_{i,t} \sim \mathcal{N}(0,\sigma_i^2)$, $z_{i,t} \sim \mathcal{N}(0,\sigma_{i,z}^2)$ and $v_{i,t} \perp z_{i,t}$. It follows from the formulas for the conditional expectation of normal random vectors that

$$\mathbb{E}[v_{i,t}|\omega_{i,t},s_{t-1},k_{t-1},\delta_{i,t}=1] = \frac{\beta_{i,t}(s_{t-1},k_{t-1})\sigma_i^2}{\beta_{i,t}^2(s_{t-1},k_{t-1})\sigma_i^2 + \sigma_{i,z}^2}\omega_{i,t}. \tag{E.9}$$

[12] Here and in the following, when we condition on $\delta_{i,t}$ we are not assuming that the variable is the agent's information. Indeed, nobody in the economy knows $\delta_{i,t}$. Rather, we are using the law of iterated expectation, which, from the point of view of the agent, is reasoning by cases. In other words, to asses his expectation conditional on some information set $\mathcal{I}$, the agent partitions $\mathcal{I}$ in $\mathcal{I} \cap \delta_{i,t} = 1$ and $\mathcal{I} \cap \delta_{i,t} = 0$ and computes the average of his expectations conditional on each information subset, weighted by their probability conditional on $\mathcal{I}$.

Note that conditional on $\delta_{i,t} = 0$, $\theta_{i,t} = \varepsilon_{i,t}$. In this case, we have $(v_{i,t}, \omega_{i,t}) = (v_{i,t}, \beta_{i,t}(s_{t-1}, k_{t-1}) \cdot \varepsilon_{i,t} + z_{i,t})$ and $\omega_{i,t}$ is a sum of variables that are independent from $v_{i,t}$. It follows that

$$\mathbb{E}[v_{i,t}|\omega_{i,t}, s_{t-1}, k_{t-1}, \delta_{i,t} = 0] = \mathbb{E}[v_{i,t}] = 0 \tag{E.10}$$

Finally, as noted after Equation (7), we have $\xi(s_{t-1}) = \Pr(\delta_{i,t} = 1)$. Substituting all these pieces into Equation (E.7) we have:

$$p_{i,t} = D_{i,t-1} + \frac{\xi_{t-1}(s_{t-1}) \cdot \beta_{i,t}(s_{t-1}, k_{t-1})\sigma_i^2}{\beta_{i,t}^2(s_{t-1}, k_{t-1})\sigma_i^2 + \sigma_{i,z}^2}\omega_{i,t} \tag{E.11}$$

Finally, substituting in our solutions for $p_{i,t}(\omega_{i,t}, s_{t-1}, k_{t-1})$ and $x_{i,t}(\theta_{i,t}, s_{t-1}, k_{t-1})$ from Equations (E.5) and (E.11) into our conjectured linear equilibrium in Equation (E.1), we obtain the following system of two equations in two unknowns ($\beta_{i,t}(s_{t-1}, k_{t-1})$ and $\lambda_{i,t}(s_{t-1}, k_{t-1})$)

$$\begin{cases} \beta_{i,t}(s_{t-1}, k_{t-1}) & = \frac{\Xi_{t-1}(k_{t-1})}{2\lambda_{i,t}(s_{t-1}, k_{t-1})} \\ \lambda_{i,t}(s_{t-1}, k_{t-1}) & = \frac{\xi_{t-1}(s_{t-1}) \cdot \beta_{i,t}(s_{t-1}, k_{t-1})\sigma_i^2}{\beta_{i,t}^2(s_{t-1}, k_{t-1})\sigma_i^2 + \sigma_{i,z}^2} \end{cases} \tag{E.12}$$

This system has a solution if and only if an equilibrium of the conjectured form exists. To find a closed form solution, obtain $\lambda_{i,t}(s_{t-1}, k_{t-1})$ from the first equation in the system and equate it to the second, obtaining

$$\frac{\Xi_{t-1}(k_{t-1})}{2\beta_{i,t}(s_{t-1}, k_{t-1})} = \frac{\xi_{t-1}(s_{t-1}) \cdot \beta_{i,t}(s_{t-1}, k_{t-1})\sigma_i^2}{\beta_{i,t}^2(s_{t-1}, k_{t-1})\sigma_i^2 + \sigma_{i,z}^2} \tag{E.13}$$

Rearranging, we obtain

$$[2\xi_{t-1}(s_{t-1}) - \Xi_{t-1}(k_{t-1})]\sigma_i^2 \beta_{i,t}^2(s_{t-1}, k_{t-1}) = \Xi_{t-1}(k_{t-1})\sigma_{i,z}^2 \tag{E.14}$$

Solving the equation for $\beta_{i,t}(s_{t-1}, k_{t-1})$ and substituting in the expression for $\lambda_{i,t}(s_{t-1}, k_{t-1})$ we obtain

$$\begin{aligned} \beta_{i,t}(s_{t-1}, k_{t-1}) &\equiv \sqrt{\frac{\sigma_{i,z}^2}{\sigma_i^2} \cdot \frac{\Xi_{t-1}(k_{t-1})}{2\xi_{t-1}(s_{t-1}) - \Xi_{t-1}(k_{t-1})}}, \\ \lambda_{i,t}(s_{t-1}, k_{t-1}) &\equiv \frac{1}{2}\sqrt{\frac{\sigma_i^2}{\sigma_{i,z}^2} \cdot \Xi_{t-1}(k_{t-1}) \cdot [2\xi_{t-1}(s_{t-1}) - \Xi_{t-1}(k_{t-1})]}\,. \end{aligned} \tag{E.15}$$

Equation (E.15) makes it clear that the existence of equilibrium requires

$$2\xi_{t-1}(s_{t-1}) > \Xi_{t-1}(k_{t-1}). \tag{E.16}$$

And it is easy to show that

$$2L > H \tag{E.17}$$

is *sufficient* to guarantee (E.16) and hence the existence of equilibrium. To see this notice that E.16 can be re-written as

$$\begin{aligned} 2(\phi_{t-1}(s_{t-1})H + (1-\phi_{t-1}(s_{t-1}))L) &> \psi_{t-1}(k_{t-1})H + (1-\psi_{t-1}(k_{t-1}) \\ L + (2\phi_{t-1}(s_{t-1}) - \psi_{t-1}(k_{t-1}))(H-L) &> 0 \end{aligned} \tag{E.18}$$

Since $H > L > 0$, the only case in which this condition may fail is when $2\phi_{t-1}(s_{t-1}) - \psi_{t-1}(k_{t-1}) < 0$. The smallest $2\phi_{t-1}(s_{t-1}) - \psi_{t-1}(k_{t-1}) < 0$ can be is -1, since ϕ_{t-1} and ψ_{t-1} are probabilities. In this case the inequality becomes

$$2L - H > 0 \tag{E.19}$$

.

Finally, we compute the equilibrium gain or loss of asset i, according to the above definition. If $x_{i,t_0} \geq 0$,

$$\begin{aligned} g_{i,t} &\equiv D_{i,t-1} - p_{i,t_0} = \textstyle\sum_{j=t_0}^{t-1} v_{i,j} - \lambda_{i,t_0}(s_{t_0-1}, k_{t_0-1}) \cdot \omega_{i,t_0} \\ &= \textstyle\sum_{j=t_0}^{t-1} v_{i,j} - \lambda_{i,t_0}(s_{t_0-1}, k_{t_0-1}) \cdot (\beta_{i,t_0}(s_{t_0-1}, k_{t_0-1}) \cdot \theta_{i,t_0} + z_{i,t_0}). \end{aligned} \tag{E.20}$$

If $x_{i,t_0} < 0$,

$$\begin{aligned} g_{i,t} &\equiv p_{i,t_0} - D_{i,t-1} = \lambda_{i,t_0}(s_{t_0-1}, k_{t_0-1}) \cdot \omega_{i,t_0} - \textstyle\sum_{j=t_0}^{t-1} v_{i,j} \\ &= \lambda_{i,t_0}(s_{t_0-1}, k_{t_0-1}) \cdot (\beta_{i,t_0}(s_{t_0-1}, k_{t_0-1}) \cdot \theta_{i,t_0} + z_{i,t_0}) - \textstyle\sum_{j=t_0}^{t-1} v_{i,j}. \end{aligned} \tag{E.21}$$