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Disposed to Be Overconfident

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ABSTRACT

We hypothesize that individuals learn about their investment ability based on realized gains and losses rather than overall portfolio performance. Thus, the disposition effect–the tendency to hold losers and sell winners–can be a source of investor overconfidence. We find that when (i) investors at a Dutch bank and (ii) investors in experiments sell more often for a gain, they exhibit overconfidence in their investment ability. Furthermore, in the experimental setting, this biased learning process leads to increased risk-taking.

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

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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)). 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, most investors will use a metric of past performance that: i) is cognitively tractable, ii) uses information that easily comes to mind, and iii) is similar to metrics used in other domains of life. For example, suppose that you ask a friend how good their favorite sports team is this season. One metric they will likely quote you is the team's win-loss record. For a retail stock investor, an analog to the win-loss record is the number of stocks sold for a gain versus the number sold for a loss. Comparing these two numbers is cognitively easy. Furthermore, for the investor who trades occasionally, realized gains and realized losses are likely to be memorable (Frydman, Barberis, Camerer, Bossaerts, and Rangel, 2014). This realized gains vs realized losses metric is appealing, but imperfect. It discards information from unrealized gains and losses. This paper documents how such biased learning can lead investors to form positively biased beliefs about their abilities.

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 and momentum (Odean, 1998b; Deaves, Lüders, and Luo, 2009; Barber and Odean, 2001; Daniel and Hirshleifer, 2015; Daniel, Hirshleifer, and Subrahmanyam, 1998). Thus, understanding the mechanisms that increase investor overconfidence may lead to improvements in investor welfare and to a better understanding of market dynamics.

The innovation of our study is that we link investor overconfidence to one of the most robust empirical patterns in selling behavior, the disposition effect: Investors are likely to realize gains more readily than losses relative to opportunities across different asset classes (e.g., equity, employee stock options, and real estate), different countries (e.g., Finland, US, and Taiwan), and investor types (individual and institutional investors) (Shefrin and Statman, 1985; Odean, 1998a; Weber and Camerer, 1998; Heath, Huddart, and Lang, 1999; Genesove and Mayer, 2001; Grinblatt and Keloharju, 2001; Frazzini, 2006; Barber, Lee, Liu, and Odean, 2007). We propose a learning process in which investors assess their ability by counting their number of realized gains and losses and discarding information from unrealized gains and losses. This learning is vulnerable to how investors sell their stocks. Realizing more gains than losses relative to opportunities, as in the disposition effect, can upwardly bias investors' beliefs about their ability.

To begin, we provide field evidence 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 actual and self-reported 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.

While our field data analysis documents a positive correlation between net realized gains and investors' confidence in their own abilities relative to others, it does not establish causality. The correlation may be due–as we claim–to investors using net gains as a signal 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 both realize more gains and rank their ability more highly.

To explore causality, we run an experiment (Experiment 1). In the 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 driving both 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.[1] 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 portfolios, 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.

[1] 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.

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 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, $p = 0.873$)).[2]

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 F. 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.

In a second step, we test the causal effect of realizations on subsequent investment behavior (Experiment 2). It is designed to directly link gain/loss realizations to risky stock investment on the extensive and intensive margin as well as overinvestment compared to an objective benchmark, which all classify as behaviors commonly associated with investor (over-)confidence (Odean, 1998b; Daniel et al., 1998; Barber and Odean, 2001; Statman, Thorley, and Vorkink, 2006; Bucher-Koenen, Alessie, Lusardi, and Van Rooij, 2025). In this experiment, subjects participate in four investment tasks. The second and third tasks are similar to the two tasks in Experiment 1 (with subjects randomly assigned to the *Selling Gains* or *Selling Losses* treatment). In the first and fourth tasks, subjects are given an endowment with which they can buy 0 to 6 risky stocks. The endowment not invested in stocks earns a risk-free return, which is lower than the expected stock return. Subjects hold their selected stocks for four periods without trading and are then paid based on stochastically determined stock prices and the risk-free interest rate. Task 1 lets us estimate idiosyncratic differences in risk-taking before treatment. And task 4 allows us to elicit subjects' tendency to invest in risky stocks after the treatment in an incentivized setting along both the extensive margin (whether to invest in

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

risky assets) and the intensive margin (how many stocks to hold). Unlike standard portfolio choice tasks, this design also permits a sharp assessment of investment optimality, which provides a measure of excessive investment/overinvestment.

We find that subjects in the *Selling Gains* condition in tasks 2 and 3 invest in more risky stocks in task 4 than subjects in the *Selling Losses* condition. This holds true for the extensive as well as intensive margin of risky investment. Subjects in the *Selling Gains* condition (i) are more likely to participate in risky stock investments and (ii) hold more risky stocks when they invest than subjects in the *Selling Losses* condition. Thus, we find direct causal evidence that gain/loss realizations affect both the decision to invest in risky assets and the intensity of investment, beyond individual investment patterns. In addition, subjects who realize mainly gains are 13.1% more likely to invest excessively in more than the optimal number of risky stocks compared to subjects who realize mainly losses. Thus, realizing gains increases risk taking along both the extensive and intensive margins and leads to systematic overinvestment relative to an experimentally optimal benchmark. This pattern suggests that realization-induced distortions in risk taking can contribute to suboptimal investment performance outside the laboratory (Barber and Odean, 2000).

Most studies in finance treat investor overconfidence as a relatively stable individual trait and abstract from the learning processes through which confidence evolves over time. We instead take a dynamic perspective and identify a learning mechanism through which investors form beliefs about their investment ability based on experienced realizations. Importantly, this mechanism creates overconfidence without requiring any type of asymmetric updating due to motivated reasoning or utility-based belief formation (Bénabou and Tirole, 2002; Köszegi, 2006; Brunnermeier and Parker, 2005). Rather, overconfidence arises mechanically from the interaction of a cognitively simple performance metric, a well-documented trading behavior—the disposition effect—and otherwise standard Bayesian updating. While a large literature shows that asymmetric updating from positive versus negative signals can generate overconfidence even under symmetric information,[3] our mechanism is conceptually distinct. It does not bias how information is processed, but which information enters the learning set: investors assess their ability using realized gains and losses rather than the full set of available information, including unrealized outcomes. As a result, the disposition effect endogenously generates an asymmetric stream of learning inputs even when belief updating itself is symmetric. Our experimental design cleanly separates biased input selection from asymmetric updating by holding constant, on average, the total number of gains and losses—realized plus unrealized—across treatments. Consequently, differences in confidence can only arise from selective reliance on realized outcomes rather

[3] There is theoretical and empirical work in economics (Bénabou and Tirole, 2002; Köszegi, 2006; Brunnermeier and Parker, 2005; Zimmermann, 2020; Eil and Rao, 2011; Saucet and Villeval, 2019; Di Tella, Perez-Truglia, Babino, and Sigman, 2015; Carlson, Maréchal, Oud, Fehr, and Crockett, 2020) and finance (Gervais and Odean, 2001) establishing that people update more strongly from positive than negative information about their beauty, generosity, intelligence, and investment ability.

than from asymmetric updating. More broadly, whereas many psychological explanations for overconfidence operate through biased interpretation or attribution of outcomes (Miller and Ross, 1975), biased recall Adler and Pansky (2020), or biased signal weighting such as confirmation bias (Wason, 1960; Rabin and Schrag, 1999; Park, Konana, Gu, Kumar, and Raghunathan, 2013), our mechanism operates at an earlier stage by shaping the information set from which beliefs about investment ability are formed.

A common criticism of the behavioral economics and behavioral finance literature is that there are too many biases and not enough effort has been made to connect them. Yet, biases and behaviors can interact in ways that magnify or offset their effects (Barberis and Thaler, 2003; Benjamin, 2019).[4] We connect two of the most prominent and well-documented biases in behavioral finance—overconfidence and the disposition effect. We document a biased learning mechanism through which the disposition effect can lead to investor overconfidence. Thus, how investors sell their stocks matters for their confidence levels.[5] 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 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. Some researchers argue that more attention improves belief accuracy and subsequent decision quality (see Gabaix (2019) for review). In contrast, others claim 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) show 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

[4]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.

[5]How investors assess 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.

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 and, in turn, increase risky stock investment at the extensive and intensive margin as well as overinvestment.

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 design and discusses our main findings from our experiments. Our empirical analyses are guided by a formal model which is reported in Appendix D. Section IV concludes.

II. Evidence from the Field

We analyze a unique data set that links confidence measures from an online survey among Dutch retail investors to two realization measures: i) investors' self-reported realizations and ii) actual realizations from individual portfolio and trades data.

A. Survey Data

We conducted an online survey of clients of a Dutch financial institution.[6] The survey was sent 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

[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.

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 self-reported 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 measured 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 asked survey participants to estimate the percentage of retail investors at the financial institution who achieved a higher annual portfolio return in 2019 than they did (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' self-reported realizations. We elicited clients' self-reports of their realizations in 2019 in an incentivized way. Survey participants could earn 10 EUR for each correct answer. We asked survey participants how many stocks they sold for a gain in the year 2019. We explained to participants that "selling for a gain" means selling for a price higher than the average purchase price of that stock. Participants were asked to indicate the number of stocks they sold for a gain. Similarly, we asked survey participants how many stocks they sold for a loss in the year 2019. We explained to participants that "selling for a loss" means selling for a price lower than the average purchase price of that stock. Participants were asked to indicate the number of stocks sold for a loss. We asked them to indicate their answers without looking up their actual sales online. We calculate the difference between the self-reported number of realized gains and losses (*Self-reported Net Gains*):

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

A positive difference indicates that the investor reports more gains than losses; a negative difference means that the investor reports fewer gains than losses; a zero difference reflects that the investor reports 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.

B. *Investor Portfolio and Trades Data*

We obtained individual portfolio and transaction-level data for 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 consist of 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.

For clients who participated in the survey, we can link the portfolio and transaction 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 satisfies these criteria, we merge the accounts.

The matching procedure followed several steps. First, we matched survey respondents' IDs with their bank client ID (4,788 unique matches, 90.6%). Those respondents we could not match in this step indicate either a gender or birth year in the survey which does not match to the bank client ID or are not linked to an investment account under that bank client ID. Afterwards, we matched those bank client IDs to their transactions. In total, we have 58,500 transactions (23,712 sales and 34,788 buys) during the period of January 01, 2013 to May 31, 2020. Of this sample, 1,479 unique bank client IDs have corresponding trades in 2019 with ISINs available in the FactSet data.

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. We obtain information on stock splits from FactSet. We calculate the difference between the number of realized gains and losses (*Net Gains*):

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

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.

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*).

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 self-reported 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. These 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 self-report, on average, that they realized 4.22 gains and 0.82 losses, with reported Net Gains of 3.40 on average.

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
Self-reported Net Gains	3.40	2.00	5.23

D. Results

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

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 reports of it (*Self-reported 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 H). 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 self-reported realizations (28.1%).

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 percentile rank among other retail investors, *Elicited Rank*, (between 0 and 100). *Net Gains* is the difference in the number of investors' realized gains and losses in 2019. *Self-reported Net Gains* is the difference in the self-reported number of investors' realized gains and losses in 2019. *Self-report Bias* is the difference between *Net Gains* and *Self-reported Net Gains*. *Actual 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 = self-report of realizations first and 0 = otherwise). *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) Elicited Rank	(2) Elicited Rank	(3) Elicited Rank	(4) Elicited Rank	(5) Elicited Rank	(6) Elicited Rank
Net Gains	0.487***	0.362**			0.790***	0.609***
	(0.15)	(0.15)			(0.23)	(0.22)
Self-reported Net Gains			0.726***	0.625***		
			(0.17)	(0.17)		
Self-report Bias					0.688***	0.635***
					(0.20)	(0.20)
Actual Rank		0.159***		0.133***		0.133***
		(0.02)		(0.03)		(0.03)
Order of Elicitation				-1.335		-1.335
				(2.04)		(2.04)
Constant	55.275***	46.685***	55.883***	50.494***	55.864***	50.487***
	(0.62)	(1.21)	(1.22)	(3.87)	(1.23)	(3.88)
N	1,479	1,479	415	415	415	415
R^2	0.01	0.06	0.03	0.07	0.03	0.07

The results in column 1 show that participants form their beliefs about their own performance relative to others based on the number of realized gains versus losses observed in their transactions. 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 percentage points ($p < 0.05$).

The effect on confidence is stronger if we test for the effect of investors' self-reported realizations – those realized 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 reported gain over a loss increases investors' rank belief by 0.63 percentage points ($p < 0.001$).

Note, beliefs about relative performance are likely formed from multiple noisy signals and investors most likely learn cumulatively from realized gains and losses over longer horizons; accordingly, the field estimates should be interpreted as attenuated correlations that reflect learning from realized outcomes over a limited horizon, understating the aggregate impact of realized outcomes on beliefs.

Further, we decompose the effect of investors' actual realized net gains and the part of self-reported realized net gains, that is biased, i.e., that deviates from the actual number of realized net gains (*Self-report Bias*) on confidence. Columns 5 and 6 show that actual realizations keep being significantly and meaningfully associated with respondents' confidence levels. Yet, how those realized gains and losses stick to investors' minds seem to matter to a similar extend. This can be reconciled with the fact that investors have the tendency to recall their gains and losses in a too positive way, which has been shown to inflate their beliefs about the investment's quality as well as their confidence in own ability (Gödker, Jiao, and Smeets, 2025). In fact, respondents in our sample exhibit a positive memory bias for realized gains and losses (Appendix G). This effect seems to reinforce our hypothesized learning process.

Lastly, an important validation of our confidence measure is whether it is systematically related to real investment behavior. A central implication of overconfidence theories is that inflated beliefs about one's ability translate into more active trading (Odean, 1998b; Daniel et al., 1998; Barber and Odean, 2001; Statman et al., 2006). In Appendix J we document that investors' beliefs about their performance-based percentile rank among other retail investors, *Elicited Rank*, is positively correlated with their total number of trades during the period of January 01, 2013 to May 31, 2020. This correlation holds when we control for their actual percentile rank among all retail clients at the financial institution, *Actual Rank*, and order of elicitation in the survey.

III. Experimental Evidence

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 experimental instructions are provided in Appendix A.[7]

A.1. Baseline Design (Experiment 1)

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}. 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

[7] The experimental design and procedures 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. The experiments were programmed and conducted with oTree (Chen, Schonger, and Wickens, 2016).

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 same 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 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 random winning stock is liquidated if the portfolio contains at least one winning stock and otherwise another random stock is liquidated. In *Selling Losses*, in each period, a random losing stock is liquidated if the portfolio contains at least one losing stock and otherwise another 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, our treatment conditions manipulate the ratio of realized gains to realized losses. Thereby, the *Selling Gains* condition generates more realized gains than realized losses, like investors experience when they exhibit the disposition effect.

In addition, because of the momentum in each stock, selling winner stocks can hurt performance in the long run. In our experiment, we virtually eliminate this effect by limiting the number of investment periods. However, in actual markets, 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 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' believe 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.

The experiment was conducted online with U.S. residents of the Prolific subject pool in May 2021. 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. This study was pre-registered at AsPredicted under ID 66925 (https://aspredicted.org/ia5zy.pdf). Table III 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, 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

Table III. Descriptive statistics for the subjects of Experiment 1.

	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 (in $)	197.97	198.00	11.34	197.92	197.00	10.82	198.01	198.50	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

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 the 18 stocks they selected in total. The average payment was $2.98, which translates to $14 per hour.

A.2. Extension to Risky Investments (Experiment 2)

In order to study the consequence of learning from gain/loss realizations for subjects' investment in risky stocks, we design Experiment 2. The experiment consists of four investment tasks with many of the features of Experiment 1. Subjects make investment decisions over several 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. In contrast to Experiment 1, an ordinary-type stock has a 30% probability of a price increase and a 70% probability of a price decrease. A high-type stock has a 70% probability of a price increase and a 30% probability of a price decrease. The price changes are similar. Price decreases are -3 or -1 with equal probability and price increases 2 or 6 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.

In tasks 2 and 3 are similar to Experiment 1. 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. In contrast to Experiment 1, after the initial portfolio selection, subjects enter four, instead of five, investment periods. Similarly to Experiment 1, each period 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 the final period, they observe the period price change for each of the stocks in their portfolio but no stocks are sold or purchased. Thus, each subject chooses eight stocks to purchase and, for each subject, three stocks are automatically sold in each of the two task trials for a total of sixteen purchases and six sales.

In Tasks 2 and 3, we implement the same *Selling Gains* and *Selling Losses* treatments between-subjects as in Experiment 1. Subjects are provided with information on both realized gains and losses as well as paper gains and losses each period. The payment scheme is identical to Experiment 1.

Afterwards, we elicit subjects' confidence after treatment, i.e., subjects' reported 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 and their belief about how many high-type stocks they selected during the investment task, as in Experiment 1.

Tasks 1 and 4 are extensions to Experiment 1. Both tasks are identical. We implement them in a pretest-posttest design, i.e., subjects participate in Task 1 prior to the treatment, i.e., Tasks 2 and 3, and in Task 4 after the treatment.[8] In this task, subjects decide to what extent they want to invest in risky stocks, which they then hold for an horizon of 4 periods. Subjects can decide to invest an endowment of $180 in 0 to 6 stocks from a new list of 20 stocks, each costing $30. The features of the stocks are the same as in Tasks 2 and 3. The endowment not invested in stocks earns a risk-free return which is framed as a certain bond investment to the subjects and is lower than the expected return of risky stocks. Each $30 "bond" earns $1.10 each period. Subjects decide on how many stocks they want to buy before seeing the list of 20 stocks and their three previous price changes. Subjects' potential payoff for each task is 1/100 of their final holdings at the end of the task trial; that is, the value, i.e., the current prices, of the stocks in the final portfolio after

[8]The empirical analysis includes the pre-treatment measure to control for individual risk preferences; the post-treatment measure is our key outcome variable.

period 4 plus the risk-free return earned on funds not invested in stocks.

Tasks 1 and 4 are designed to isolate how treatment-induced belief changes translate into subsequent risky investment behavior. These tasks allow us to measure risk-taking in an incentivized setting along both the extensive margin (whether to invest in risky assets) and the intensive margin (how many stocks to hold). Unlike standard portfolio choice tasks, this design also permits a sharp assessment of investment optimality. Given the experimental parameters, a risk-neutral subject who correctly infers stock quality and applies the optimal selection rule maximizes expected wealth by investing in exactly three risky stocks.[9] Intuitively, while high-type stocks offer positive expected returns, the posterior probability that a selected stock is high type declines as additional stocks are added, implying diminishing, and eventually negative, marginal expected returns beyond the third investment. This structure allows us to distinguish changes in risk-taking driven by distorted beliefs relative to optimal responses in the investment environment, providing a natural measure of overinvestment.

The experiment was conducted online with U.S. residents of the Prolific subject pool in September 2025. In both treatments, subjects had to participate in four trials of investment tasks. Their payoff depended on their choices and on the randomly generated price changes for stocks in their portfolio in one of the four task trials. At the end of the experiment, one of the four task trials was randomly selected for payment. In addition, subjects received a fixed participation fee of \$1. The average payment was \$3.02. We used the same five comprehension questions to test the subjects' understanding of the experimental instructions as in Experiment 1. We excluded subjects from the experiment who gave an incorrect answer to more than one comprehension question.

A total of 602 subjects participated in the experiment, 318 subjects in treatment *Selling Gains* and 284 in treatment *Selling Losses*. Participating in the experiment took a median time of 12 minutes and 27

[9] Consider the experimental environment with 20 assets, of which exactly 5 are high type and 15 are ordinary type. Conditional on type, asset returns are independent across time and assets. In each period, an "up" move occurs with probability 0.7 (high type) or 0.3 (ordinary type); conditional on an up (down) move, the price change is +2 or +6 (respectively −1 or −3) with equal probability. Hence $E[\Delta \mid \text{up}] = 4$ and $E[\Delta \mid \text{down}] = -2$, implying

$$E[\Delta \mid H] = 0.7 \cdot 4 + 0.3 \cdot (-2) = 2.2, \qquad E[\Delta \mid O] = 0.3 \cdot 4 + 0.7 \cdot (-2) = -0.2,$$

so over the four post-treatment periods $E[P_4 \mid H] = 30 + 4 \cdot 2.2 = 38.8$ and $E[P_4 \mid O] = 30 + 4 \cdot (-0.2) = 29.2$. Subjects observe three prior price changes per asset and apply a monotone selection rule that ranks assets by the number of past upward moves; under Bayes' rule, the posterior probability of high type is increasing in the number of prior ups (e.g., $P(H \mid U = 3) \approx 0.81$ and $P(H \mid U = 2) \approx 0.44$). Uninvested endowment earns 1.10 per period per \$30 (i.e., \$4.40 over four periods), so choosing $k \in \{0, \ldots, 6\}$ assets yields expected final wealth

$$E[W(k)] = 180 + E\left[\sum_{j=1}^{k}(P_{4,j} - 30)\right] + 4.40 \cdot (6 - k).$$

Evaluating $E[W(k)]$ under the stated selection rule gives $E[W(0)] = 206.40$, $E[W(1)] = 208.92$, $E[W(2)] = 210.61$, $E[W(3)] = 211.15$, $E[W(4)] = 210.75$, $E[W(5)] = 209.75$, and $E[W(6)] = 208.20$, so the risk-neutral optimum is $k^* = 3$. The marginal expected return becomes negative beyond the third asset because the additional selected assets have a sufficiently low posterior probability of being high type. For risk-averse subjects, the optimal number of stocks to select might be lower, depending on the risk aversion parameter.

seconds. This study was pre-registered at AsPredicted under ID 247713 (https://aspredicted.org/jj2bh5.pdf). Table AI in the Appendix reports descriptive statistics. Our sample consists of 56% female subjects. On average, subjects were 46 years old (min. 20 years and max. 84 years).

B. Results

The results from our experiments provide evidence for a learning process which biases subjects' level of confidence about their ability to invest (Experiment 1), which extends to subsequent higher investments in risky stocks (Experiment 2). The results are consistent with a model in which investors form their beliefs about their investment ability by counting the number of gains and losses they have realized.[10]

B.1. Learning about Investment Ability Based on Realized Gains and Losses (Experiment 1)

Result 2. *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 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 AXI 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.[11]

Result 3. *Subjects form beliefs about their own ability to invest based on realized gains and losses rather than overall portfolio performance.*

[10] To formalize the investors' biased learning process and its implications, we develop a theoretical model. Refer to Appendix ?? for the model. The model produces two 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 Experiment 1. Second, investor overconfidence, generated by the biased learning process, leads to excessive trading with lower trading profits. This result is consistent with the findings from our Experiment 2.

[11] 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 III.

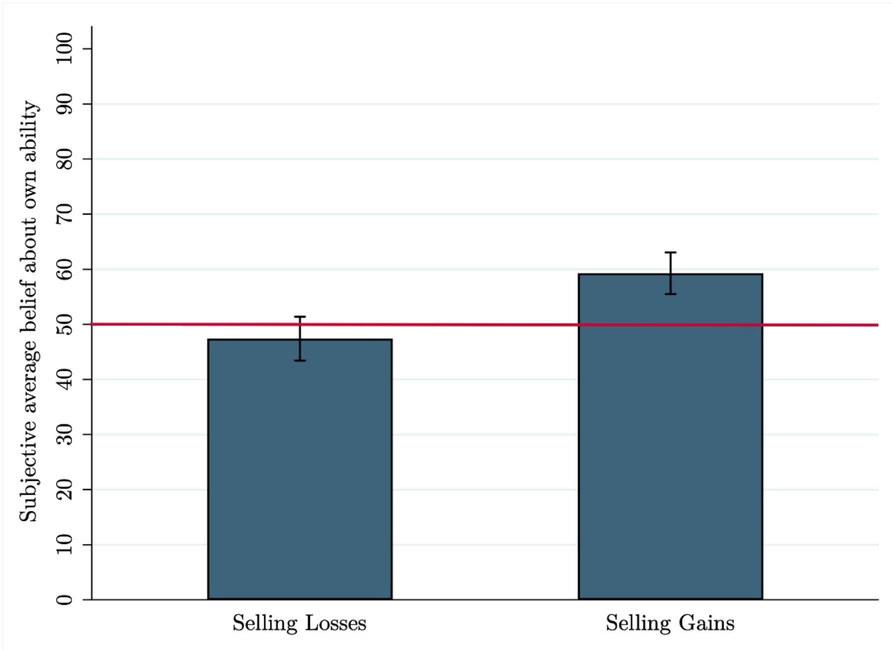

Figure 1. Average beliefs about own ability. This figure displays mean values of subjects' belief about own ability measured by subjects' elicited likelihood in percent of being ranked in the upper half of a group of 10 participants based on performance in the task (from 0% to 100%). The bars represent 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%).

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

Column 2 of Table IV 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.

Result 4. *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

Table IV. 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. *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***	8.946	19.315	49.004***	37.901***
	(2.02)	(25.28)	(25.54)	(5.90)	(3.33)
N	301	301	301	301	301
R^2	0.06	0.06	0.09	0.08	0.21

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.

In Table IV, 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 IV, 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.

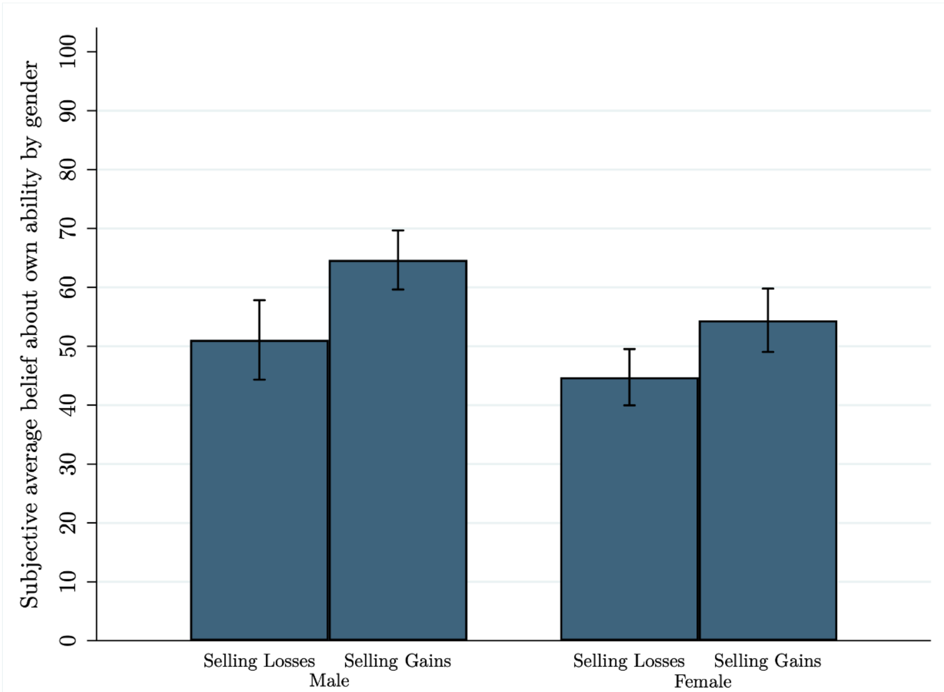

Figure 2. Average beliefs about own ability by gender. This figure displays mean values of subjects' belief about own ability measured by subjects' elicited likelihood in percent of being ranked in the upper half of a group of 10 participants based on performance in the task (from 0% to 100%). The bars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

The coefficient of the treatment dummy remains significantly positive.

Result 5. *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, which resembles a disposition effect-like selling pattern. 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, $p = 0.000$).[12]

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.

[12] Note that when increasing sample size, and thus power, we see that the there is a pronounced and significant effect in both directions. Realizing mainly gains results, on average, in overconfidence, whereas realizing mainly losses results, on average, in underconfidence (see Figure AI in the Appendix).

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 AXI 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 V. 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. *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***	1.186	1.299	1.310
	(0.31)	(3.74)	(3.76)	(3.82)
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 V 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 III, 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 V 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).

B.2. Impact on Risky Stock Investments (Experiment 2)

In various settings–ranging from theoretical frameworks to experimental and actual markets–overconfident investors have been shown to trade more than is in their own best interest (Odean, 1998b; Daniel et al., 1998; Weber and Camerer, 1998; Barber and Odean, 2001; Deaves et al., 2009; Daniel and Hirshleifer, 2015). Experiment 2 provides direct evidence that our identified learning mechanism is a microfoundation of investor overconfidence when more gains than losses are realized, which also leads to more risky investments, and even over-investment compared to an objective benchmark.[13]

Result 6. *Subjects invest in more risky stocks if more gains were realized than if more losses were realized.*

The key outcome measure for our subsequent analysis is subjects' investment in risky stocks in Experiment 2 Task 4. Subjects could choose to invest an endowment into up to 6 stocks. Money not invested in stocks earned risk-free interest.

Figure 3 shows the average number of stocks subjects invested in after the treatment. On average, subjects in the *Selling Gains* treatment invest in significantly more risky stocks than subjects in the *Selling Losses* treatment (t-test, $p < 0.001$). Subjects for whom mainly gains were realized, invest in 3.6 stocks, whereas subjects for whom mainly losses were realized, invest in 3.1 stocks (out of 6). Subjects invest in about half a stock more in the *Selling Gains* treatment compared to the *Selling Losses* treatment.

This finding is supported in a regression analysis. Table VI provides coefficients from linear estimates of subjects' investments in risky assets. Column 1 documents the treatment effect. The coefficient of the treatment dummy is significantly positive, that is, subjects in the *Selling Gains* treatment invest in significantly more risky stocks. In column 2, the treatment effect remains when controlling for subjects' portfolio performance, gender, and pre-treatment (Task 1) investments.[14]

[13] Consistent with these findings, Dutch retail investors' realizations (*Net Gains* and *Self-reported Net Gains*) are significantly positively correlated with their trading frequency in our field data. Please see Table AVII in the Appendix for the detailed analysis.

[14] The mean portfolio performance is above 200. Thus the coefficient on portfolio performance of 0.9 times the mean portfolio performance offsets the negative intercept of -1.369. Thus our assumption of linearity in the pre-round investment's influence

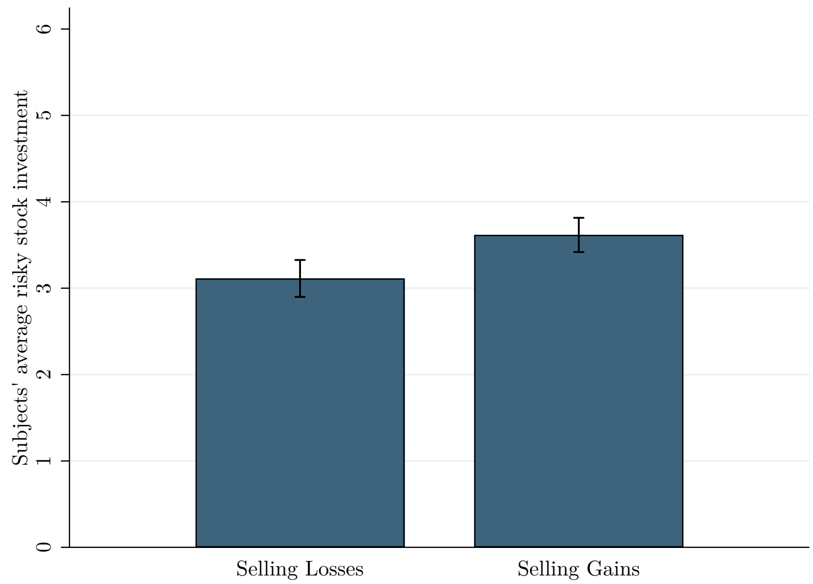

Figure 3. Average investment in risky stocks. This figure displays the average number of stocks subjects invested in after the treatment (from 0 to 6). The bars represent the mean values by treatment. Error bars indicate 95% confidence intervals.

In addition, the table reports how the treatment affects the extensive and intensive margin of risky investments. Realizing mainly gains increases both subjects' extensive and intensive margin of risky investments compared to realizing mainly losses (Column 3 and 5). Controlling for portfolio performance, gender, and pre-treatment investments, being assigned to the treatment increases the probability of investing in at least one risky stock by about 4.9 percentage points (Column 4). Thus, the *Selling Gains* treatment has a statistically significant positive effect on participation, which is not driven by pre-existing investments. Further, conditional on prior investment intensity, subjects in the *Selling Gains* treatment invest in about 0.24 additional risky stocks compared to subjects in the *Selling Losses* treatment (Column 6). The treatment increases investment intensity within-investor, over and above individuals' baseline propensity to hold risky stocks.

Finally, we study the treatment effect on subjects' optimality when investing after the treatment. Given the experimental parameters and assuming that subjects follow the correct rule to select high-type stocks and are risk neutral, subjects' optimal choice is to select three stocks (see Section III.A.2). For risk-averse subjects, the optimal number of stocks to select might be lower, depending on the risk aversion parameter. Subjects who realize mainly gains are significantly more likely to invest excessively in more than three risky stocks after the treatment compared to subjects who realize mainly losses (column 7). Controlling for

on the post-round investment does not imply that people who do not invest in the pre-round invest significantly negatively in the post-round.

Table VI. Risky stock investment. This table contains the coefficients and robust standard errors (in parentheses) of OLS regression. The dependent variables are *Invest*, the number of stocks subjects invested in after the treatment (from 0 to 6), *Invest Ext.*, a dummy variable indicating the extensive margin, i.e., whether a subject invested in risky stocks after the treatment with 1 if the subject invested in at least one stock and 0 otherwise, and *Invest Int.*, the intensive margin, i.e., the number of stocks subjects invested in after the treatment if they invested (from 1 to 6), *Invest Exc.*, a dummy variable indicating excessive trading with 1 if the subject invested in more than three stocks after the treatment and 0 otherwise. *Treatment* is a dummy variable representing our treatment with 1 = Selling Gains and 0 = Selling Losses. *Portfolio Performance* is subjects' average portfolio performance in the two treatment investment trials, including paper gains and losses and the cash position. *Female* is a dummy variable indicating subjects' gender with 1 if the subject is female and 0 otherwise. *Invest (Pre)* is subjects' number of stocks invested in Task 1 before the treatment (from 0 to 6). *Invest Ext. (Pre)* is a dummy variable indicating whether a subject invested in risky stocks in Task 1 before the treatment with 1 if the subject invested in at least one stock and 0 otherwise.*, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) Invest	(2) Invest	(3) Invest Ext.	(4) Invest Ext.	(5) Invest Int.	(6) Invest Int.	(7) Invest Exc.	(8) Invest Exc.
Treatment	0.504^{***}	0.327^{***}	0.055^{**}	0.049^{**}	0.335^{***}	0.237^{***}	0.131^{***}	0.089^{***}
	(0.15)	(0.11)	(0.03)	(0.02)	(0.12)	(0.09)	(0.04)	(0.03)
Portfolio Performance		0.009^{**}		0.000		0.008^{**}		0.002^{*}
		(0.00)		(0.00)		(0.00)		(0.00)
Female		0.005		-0.004		-0.134		-0.013
		(0.11)		(0.02)		(0.09)		(0.03)
Invest (Pre)		0.727^{***}				0.619^{***}		0.171^{***}
		(0.04)				(0.04)		(0.01)
Invest Ext. (Pre)				0.661^{***}				
				(0.06)				
Constant	3.113^{***}	-1.369	0.838^{***}	0.233	3.714^{***}	-0.447	0.419^{***}	-0.681^{**}
	(0.11)	(1.02)	(0.02)	(0.21)	(0.09)	(0.80)	(0.03)	(0.29)
N	602	602	602	602	522	522	602	602
R^2	0.02	0.44	0.01	0.29	0.02	0.44	0.02	0.34

portfolio performance, gender, and pre-treatment investments, being assigned to the treatment increases the probability of investing excessively in more than three risky stocks by about 13.1 percentage points (Column 8). Thus, realizing more gains than losses does not only increase risk taking along both the extensive and intensive margins, it also leads to systematic over-investment relative to the experimentally optimal benchmark. These findings suggest that realization-induced distortions in risk taking may contribute to suboptimal investment performance outside the laboratory (Barber and Odean, 2000).

This is in line with a formal model (extending Kyle (1985) and Gervais and Odean (2001)) embedding this learning process in a trading environment, which we outline in detail in Appendix D. We model a market with a retail investor, a professional investor, a noise trader, and a competitive market maker. Each period, the investors receive independent signals about the next period's dividend for a risky asset. And each period, the retail investor sells one of the assets in his portfolio for a gain with probability χ and for a loss with probability $1 - \chi$. The retail investor could rationally estimate his ability from the history of his signals and realized dividends. Instead, he estimates his ability from the history of his realized gains and losses. We derive a closed-form solution for the equilibrium and prove three propositions: i) An increase in the tendency of the retail investor to sell for a gain (i.e., an increase in χ) leads the retail investor to become more confident in the accuracy of his signal; ii) An increase in the tendency of the retail investor to sell for a gain leads the retail investor to trade more aggressively, and iii) An increase in the tendency of the investor to sell for a gain leads to lower profits when the rate at which he sells for a gain is greater than the rate at which his signal is true. Furthermore, when the retail investor's overconfidence is sufficiently high, his profits are negative.

C. Robustness

C.1. Robustness to Explicit Knowledge of the Selling Mechanism (Experiment 3)

Our manipulation of gain and loss realizations in the experiment may have had an unintended consequence on subjects' belief formation because the mechanism behind which stock was chosen to be sold was not revealed to subjects. Subjects may have drawn inference from the liquidation selection itself. In order to rule out this concern, we ran a third experiment, in which we inform subjects explicitly about the selling mechanism, i.e., by which rule the computer sells stocks. In the *Selling Gains* condition, we tell them that one of the stocks is sold by the computer program at the stock's current price. and that, when possible, the computer selects a stock to sell that is currently at a gain (i.e., the price is above \$30). In the *Selling Losses* condition, we tell them that one of the stocks is sold by the computer program at the stock's current price and that, when possible, the computer selects a stock to sell that is currently at a loss (i.e., the price is below \$30). Appendix C shows screenshots of these instructions. Otherwise, the experimental design and procedures are the same as in Experiment 1.

The experiment was conducted online with U.S. residents of the Prolific subject pool in January 2025. 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. 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. The average payment was \$2.94. We used the same five comprehension questions to test subjects' understanding of the experimental instructions as in Experiment 1. We excluded subjects from the experiment who gave an incorrect answer to more than one comprehension question.

A total of 305 subjects participated in the experiment, 160 subjects in the treatment *Selling Gains* and 145 in the treatment *Selling Losses*. Participating in the experiment took a median time of 10 minutes. This study was pre-registered at AsPredicted under ID 210275 (https://aspredicted.org/jj32fc.pdf). Table AII in the Appendix reports descriptive statistics. Our sample consists of 51% female subjects. On average, subjects were 39 years old (min. 18 years and max. 73 years).

We replicate our treatment effect. 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 61.34%, whereas subjects for whom mainly losses were realized, indicate a mean belief of 42.94%. See Table AX in the Appendix for more details replicating the findings of Table AXI from Experiment 1. Moreover, we find the same pattern for subjects' belief about how many high-type stocks they have selected (see Table AXII in the Appendix). Subjects in the *Selling Gains* treatment believe to have selected significantly more high-type stocks than subjects in the *Selling Losses* treatment, on average 2.3 stocks more (t-test, $p = 0.000$).

C.2. Replication Across Experiments and Pooled Results

Across our three experiments, we replicate our treatment effect on confidence. For Experiment 2 we include the results from Tasks 2 and 3. Table VII reports the treatment effect in each experiment and tests for differences between experiments. The detailed regression results are reported in Appendix L.

The treatment effect is the coefficient on the treatment dummy from an OLS regression with subjects' confidence in own ability (*Belief Ability*) as dependent variable. The last column reports results from a Wald χ^2 test of equality of treatment effects across the three experiments based on the estimated coefficients and their standard errors. Experiment 1 appears to understate the effect size of the treatment effect, but the differences between experiments are not statistically significant ($p = 0.207$).

In the pooled sample, we estimate a treatment effect of 15.97. On average across the three experiments, subjects in the *Selling Gains* treatment report a confidence in their investment ability that is 15.97 percentage points higher than for subjects in the *Selling Losses* treatment (t-test, $p = 0.000$). Note that when increasing sample size, and thus power, we see that the there is a pronounced and significant effect in both directions. Realizing mainly gains results, on average, in overconfidence, whereas realizing mainly losses results, on average, in underconfidence (see Figure AI in the Appendix). Subjects for whom mainly gains were realized, indicate a mean belief of 60.68% that they would be in the top half of a group of ten subjects if they participated in a repeat experiment, whereas subjects for whom mainly losses were realized, indicate a mean belief of 44.70%.

Note that attrition rates do not differ significantly across treatments in all three of our experiments, and observable pre-treatment characteristics are well balanced. Crucially, the majority of exclusions (due to failed comprehension checks) occurred before subjects experienced the treatment manipulation (see Appendix K).

Table VII. Replication across the three experiments.

Experiment	Treatment effect	Standard error	Sample size	Wald test of equality of treatment effects
Experiment 1	11.872	2.82	301	
Experiment 2	16.893	1.93	602	$\chi^2(2) = 3.153$
Experiment 3	18.399	2.69	305	$p = 0.207$
Pooled experiments	15.974	1.37	1,208	

IV. Conclusion

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. Thus the tendency to realize gains more readily than losses leads investors who use net realized gains as a performance metric to overestimate their past performance, which in turn can lead to overconfidence about ability and future performance.

In our experiments, we document the causal effect of gain/loss realizations on individuals' confidence as well as on subsequent investment behavior. Controlling for actual performance on the investment task, subjects randomly assigned to our *Selling Gains* condition–in which mainly gains are realized during the experiment–are subsequently more confident in their ability 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. Finally, we document that gain/loss realizations also causally affect risky stock investments. Subjects in the *Selling Gains* condition, who realized mainly gains during the task, invest more in risky stocks afterwards than subjects in the *Selling Losses* condition.

We conclude that when learning about their own investment ability investors use a metric based on the realizations of gains and losses. 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. Investors with this learning metric and the disposition effect will be 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.

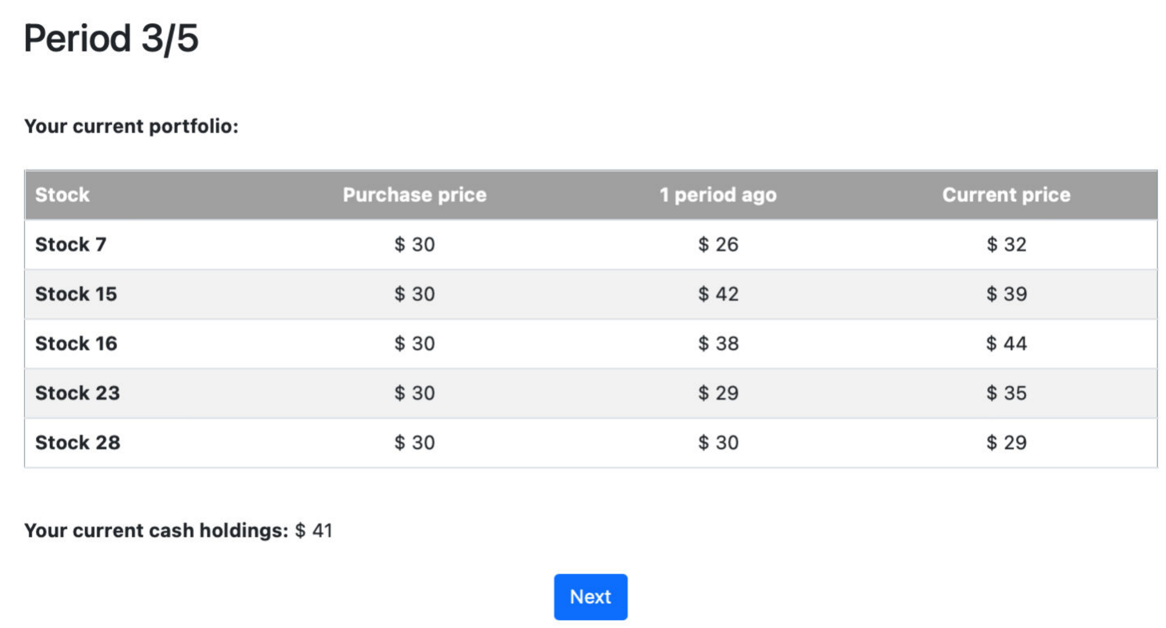
As in period 1, the list contains exactly 3 ordinary-type stocks and exactly 1 high-type stock. You are not told which stock is of which type. However, for each of the 4 stocks, you are shown price changes from the three previous periods.

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. Revised Experimental Instructions for Experiment 3

Instructions of Investment Task

You start with your initial portfolio and enter five sequential investment periods.

Periods 1-4

Each period, you first 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 sold by the computer program at the stock's current price. **When possible, the computer selects a stock to sell that is currently at a gain (i.e., above $30)**.

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.

Period 5

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

Next

Experimental instructions in *Selling Gains* condition of Experiment 3.

Instructions of Investment Task

You start with your initial portfolio and enter five sequential investment periods.

Periods 1-4

Each period, you first 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 sold by the computer program at the stock's current price. **When possible, the computer selects a stock to sell that is currently at a loss (i.e., below $30)**.

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.

Period 5

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

Next

Experimental instructions in *Selling Losses* condition of Experiment 3.

D. The Model

The model formalizes a learning mechanism through which retail investors infer their investment ability from realized trading outcomes. A retail investor receives noisy signals about asset payoffs and is uncertain about his own ability, defined as the probability that his signals are informative. A fully rational agent would learn about ability by tracking the frequency of correct signals. Instead, we assume that the investor evaluates performance using a simple and salient proxy—the number of realized gains relative to realized losses—which is observable but imperfectly related to true decision quality. When investors exhibits a disposition effect and realize gains more frequently than losses, this proxy overstates success relative to the underlying signal quality. The retail investor nonetheless applies a standard Bayesian updating rule to this distorted statistic, which leads to upward-biased beliefs about ability. Embedding this learning process in a trading environment implies that higher rates of gain realization increase perceived ability as well as trading aggressiveness, and can reduce expected profits once perceived ability exceeds true ability. Sufficiently high overconfidence in ability results in negative expected profits. The model thus isolates a belief-based channel through which gain and loss realizations affect investor confidence and trading behavior.

A. Dividends

A single risky asset is traded for $t = 1, \ldots, T$. Dividends follow

$$D_t = D_{t-1} + v_t^R + v_t^P, \tag{D.1}$$

where the component innovations are independent and Gaussian:

$$v_t^R \sim N(0, \sigma_c^2), \qquad v_t^P \sim N(0, \sigma_c^2), \qquad v_t^R \perp v_t^P, \tag{D.2}$$

and $\{(v_t^R, v_t^P)\}_{t\geq 1}$ are i.i.d. over time.

B. Signal technologies

The Retail Investor. The Retail Investor has time-invariant ability $a \in \{L, H\}$ with $0 < L < H < 1$ and common prior

$$\mathbb{P}(a = H) = \phi_0 \in [0, 1]. \tag{D.3}$$

Conditional on a, the Retail Investor's informativeness indicator $\delta_t^R \in \{0,1\}$ satisfies

$$\mathbb{P}(\delta_t^R = 1 \mid a) = a, \qquad \{\delta_t^R\}_{t\geq 1} \text{ i.i.d. over time.} \tag{D.4}$$

His period-t signal about *his own dividend component* is

$$\theta_t^R = \delta_t^R v_t^R + (1-\delta_t^R)\varepsilon_t^R, \qquad \varepsilon_t^R \sim N(0,\sigma_c^2), \qquad \varepsilon_t^R \perp v_t^R. \tag{D.5}$$

Self-normalization: v_t^R and ε_t^R share the same distribution, so $\theta_t^R \sim N(0,\sigma_c^2)$ regardless of δ_t^R.

The Professional Investor. The Professional Investor has known signal quality $a^P \in (0,1)$ satisfying

$$0 < L < H < a^P < 1, \tag{D.6}$$

and $\delta_t^P \in \{0,1\}$ is i.i.d. with

$$\mathbb{P}(\delta_t^P = 1) = a^P. \tag{D.7}$$

His period-t signal about *his own dividend component* is

$$\theta_t^P = \delta_t^P v_t^P + (1-\delta_t^P)\varepsilon_t^P, \qquad \varepsilon_t^P \sim N(0,\sigma_c^2), \qquad \varepsilon_t^P \perp v_t^P. \tag{D.8}$$

Again, self-normalization implies $\theta_t^P \sim N(0,\sigma_c^2)$ regardless of δ_t^P.

Independence summary. For each t, the collections $(v_t^R, \varepsilon_t^R, \delta_t^R)$, $(v_t^P, \varepsilon_t^P, \delta_t^P)$, and the noise demand z_t are mutually independent. Consequently $\theta_t^R \perp \theta_t^P$.

C. Information and timing within a period

Let $\mathcal{F}_{t-1}$ denote public information up to (but not including) trading in period t. The timeline within period t is:

1. The Retail Investor observes (θ_t^R, k_{t-1}) and submits an order x_t^R. (k_{t-1} is defined below.)
2. The Professional Investor observes (θ_t^P, k_{t-1}) and submits an order x_t^P.
3. Noise demand $z_t \sim N(0,\sigma_z^2)$ is realized. Total order flow is $\omega_t = x_t^R + x_t^P + z_t$.
4. The Market Maker observes (ω_t, k_{t-1}) and sets the competitive price $p_t = \mathbb{E}[D_t \mid \omega_t, \mathcal{F}_{t-1}, k_{t-1}]$.
5. Payoffs are realized. Profits are $\pi_t^R = x_t^R(D_t - p_t)$ and $\pi_t^P = x_t^P(D_t - p_t)$.

All strategic traders are risk neutral and maximize one-period expected profits.

D. *Biased learning: the binomial assumption*

At the start of each period period u, the retail investor realizes (sells) a position in his portfolio. Let $G_u \in \{0, 1\}$ be the indicator that the Retail Investor realizes a gain at the start of period u (before trading in u). We adopt the reduced-form assumption:

$$\mathbb{P}(G_u = 1) = \chi, \qquad \{G_u\}_{u \geq 1} \text{ i.i.d. over time.} \tag{D.9}$$

Define $k_{t-1} := \sum_{u=1}^{t-1} G_u$. Then

$$k_{t-1} \sim \text{Binomial}(t-1, \chi). \tag{D.10}$$

The Retail Investor's biased perceived signal quality. The Retail Investor starts with the common prior $\mathbb{P}(a = H) = \phi_0 \in [0, 1]$. He could rationally update by observing how many times he receives an informative signal in t periods. However he updates *as if* k_{t-1} were the number of informative signals. Define

$$\psi_{t-1}(k) := (a = H \mid K_{t-1} = k) = \frac{H^k (1-H)^{t-1-k} \phi_0}{H^k (1-H)^{t-1-k} \phi_0 + L^k (1-L)^{t-1-k} (1-\phi_0)}, \tag{D.11}$$

and the resulting biased perceived informativeness

$$\Xi_{t-1}(k) := (a \mid K_{t-1} = k) = \psi_{t-1}(k) H + [1 - \psi_{t-1}(k)] L \in [L, H]. \tag{D.12}$$

Rational benchmark probability for the retail signal to be informative. For the Professional Investor and the Market Maker, the rational probability that $\delta_t^R = 1$ remains at the prior mean

$$\xi_0 := \mathbb{E}[a] = \phi_0 H + (1 - \phi_0) L. \tag{D.13}$$

This ξ_0 is common knowledge and does not depend on t or k.

E. *Linear equilibrium with two signals (conditioning on k_{t-1})*

Fix t and a realized $k := k_{t-1}$. A (symmetric-in-form) linear equilibrium consists of coefficients

$$\beta_t^R(k), \ \beta_t^P(k), \ \lambda_t(k)$$

such that:

1. The Retail Investor submits $x_t^R = \beta_t^R(k)\theta_t^R$.
2. The Professional Investor submits $x_t^P = \beta_t^P(k)\theta_t^P$.
3. The Market Maker sets $p_t = D_{t-1} + \lambda_t(k)\omega_t$ where $\omega_t = x_t^R + x_t^P + z_t$.
4. Given the price rule, each trader's order is optimal, conditional on the trader's information and beliefs, and the price equals the conditional expectation $p_t = \mathbb{E}[D_t \mid \omega_t, \mathcal{F}_{t-1}, k]$.

Step 1: The Retail Investor's best response Fix k and conjecture that the price rule is $p_t = D_{t-1}+\lambda\omega_t$ with $\lambda > 0$. Given x_t^P and z_t, The Retail Investor's one-period profit is

$$\pi_t^R = x_t^R\big(v_t^R + v_t^P - \lambda(x_t^R + x_t^P + z_t)\big). \tag{D.14}$$

Conditional on (θ_t^R, k), v_t^P has mean 0 and is independent. The biased conditional mean of v_t^R is

$$[v_t^R \mid \theta_t^R, k] = \Xi_{t-1}(k)\,\theta_t^R. \tag{D.15}$$

(Reason: if $\delta_t^R = 1$, then $v_t^R = \theta_t^R$; if $\delta_t^R = 0$, then v_t^R is mean-zero independent of θ_t^R; and the biased belief assigns probability $\Xi_{t-1}(k)$ to $\delta_t^R = 1$.)
Thus, conditional on (θ_t^R, k), The Retail Investor chooses x_t^R to maximize

$$[\pi_t^R \mid \theta_t^R, k] = x_t^R\,\Xi_{t-1}(k)\theta_t^R - \lambda(x_t^R)^2, \tag{D.16}$$

where we used $[x_t^P + z_t \mid \theta_t^R, k] = 0$. The first-order condition implies

$$x_t^R = \frac{\Xi_{t-1}(k)}{2\lambda}\theta_t^R \qquad \Rightarrow \qquad \beta_t^R(k) = \frac{\Xi_{t-1}(k)}{2\lambda}. \tag{D.17}$$

Step 2: The Professional Investor's best response By the same logic, the rational conditional mean satisfies

$$\mathbb{E}[v_t^P \mid \theta_t^P] = a^P\theta_t^P, \tag{D.18}$$

and v_t^R is mean-zero independent of θ_t^P. Therefore The Professional Investor maximizes

$$\mathbb{E}[\pi_t^P \mid \theta_t^P, k] = x_t^P\,a^P\theta_t^P - \lambda(x_t^P)^2, \tag{D.19}$$

implying

$$x_t^P = \frac{a^P}{2\lambda}\theta_t^P \qquad \Rightarrow \qquad \beta_t^P(k) = \frac{a^P}{2\lambda}. \tag{D.20}$$

Step 3: The Market Maker's pricing rule The Market Maker sets $p_t = \mathbb{E}[D_t \mid \omega_t, \mathcal{F}_{t-1}, k] = D_{t-1} + \mathbb{E}[v_t^R + v_t^P \mid \omega_t, k]$.

Fix k and hence fix $\beta_t^R(k)$ and $\beta_t^P(k)$. Because of self-normalization,

$$\theta_t^R \sim N(0, \sigma_c^2) \text{ regardless of } \delta_t^R, \qquad \theta_t^P \sim N(0, \sigma_c^2) \text{ regardless of } \delta_t^P,$$

and $\theta_t^R \perp \theta_t^P \perp z_t$. Hence, conditional on k,

$$\omega_t = \beta_t^R(k)\theta_t^R + \beta_t^P(k)\theta_t^P + z_t \sim N\big(0,\ \sigma_c^2\big((\beta_t^R(k))^2 + (\beta_t^P(k))^2\big) + \sigma_z^2\big), \tag{D.21}$$

and the distribution of ω_t does *not* depend on (δ_t^R, δ_t^P). Therefore $\mathbb{P}(\delta_t^R = 1 \mid \omega_t, k) = \mathbb{P}(\delta_t^R = 1) = \xi_0$ and $\mathbb{P}(\delta_t^P = 1 \mid \omega_t, k) = a^P$.

Conditional expectation. Using the law of total expectation and the bivariate normal projection under $\delta = 1$:

$$\begin{aligned} \mathbb{E}[v_t^R \mid \omega_t, k] &= \xi_0 \cdot \mathbb{E}[v_t^R \mid \omega_t, k, \delta_t^R = 1] + (1 - \xi_0) \cdot \mathbb{E}[v_t^R \mid \omega_t, k, \delta_t^R = 0] \\ &= \xi_0 \cdot \frac{(v_t^R, \omega_t \mid k, \delta_t^R = 1)}{\mathrm{Var}(\omega_t \mid k)}\, \omega_t, \end{aligned} \tag{D.22}$$

because if $\delta_t^R = 0$ then v_t^R is independent of ω_t and the conditional mean is 0. When $\delta_t^R = 1$, $\theta_t^R = v_t^R$, so

$$(v_t^R, \omega_t \mid k, \delta_t^R = 1) = (v_t^R, \beta_t^R(k) v_t^R) = \beta_t^R(k)\sigma_c^2.$$

Similarly,

$$\mathbb{E}[v_t^P \mid \omega_t, k] = a^P \cdot \frac{\beta_t^P(k)\sigma_c^2}{\mathrm{Var}(\omega_t \mid k)}\, \omega_t.$$

Therefore

$$\mathbb{E}[v_t^R + v_t^P \mid \omega_t, k] = \lambda\, \omega_t, \qquad \lambda = \frac{\sigma_c^2\big(\xi_0\, \beta_t^R(k) + a^P\, \beta_t^P(k)\big)}{\sigma_c^2\big((\beta_t^R(k))^2 + (\beta_t^P(k))^2\big) + \sigma_z^2}. \tag{D.23}$$

Step 4: Solving for $(\lambda_t(k), \beta_t^R(k), \beta_t^P(k))$ Fix k and write $\Xi := \Xi_{t-1}(k)$ for brevity. Combine (D.17), (D.20), and (D.23). Substitute $\beta_t^R(k) = \Xi/(2\lambda)$ and $\beta_t^P(k) = a^P/(2\lambda)$ into (D.23) to obtain:

$$\begin{aligned}\lambda &= \frac{\sigma_c^2\left(\xi_0 \frac{\Xi}{2\lambda} + a^P \frac{a^P}{2\lambda}\right)}{\sigma_c^2\left(\left(\frac{\Xi}{2\lambda}\right)^2 + \left(\frac{a^P}{2\lambda}\right)^2\right) + \sigma_z^2} \\ &= \frac{\sigma_c^2\left(\xi_0\Xi + (a^P)^2\right)/(2\lambda)}{\sigma_c^2\left(\Xi^2 + (a^P)^2\right)/(4\lambda^2) + \sigma_z^2}. \end{aligned} \tag{D.24}$$

Multiply both sides by the denominator and simplify:

$$\begin{aligned}\lambda\left(\frac{\sigma_c^2(\Xi^2 + (a^P)^2)}{4\lambda^2} + \sigma_z^2\right) &= \frac{\sigma_c^2\left(\xi_0\Xi + (a^P)^2\right)}{2\lambda} \\ \frac{\sigma_c^2(\Xi^2 + (a^P)^2)}{4\lambda} + \lambda\sigma_z^2 &= \frac{\sigma_c^2\left(\xi_0\Xi + (a^P)^2\right)}{2\lambda} \\ \sigma_c^2(\Xi^2 + (a^P)^2) + 4\lambda^2\sigma_z^2 &= 2\sigma_c^2\left(\xi_0\Xi + (a^P)^2\right) \\ 4\lambda^2\sigma_z^2 &= \sigma_c^2\left((a^P)^2 + 2\xi_0\Xi - \Xi^2\right). \end{aligned} \tag{D.25}$$

Hence

$$\boxed{\lambda_t(k) = \frac{\sigma_c}{2\sigma_z}\sqrt{(a^P)^2 + 2\xi_0\,\Xi_{t-1}(k) - \Xi_{t-1}(k)^2}}, \tag{D.26}$$

and

$$\boxed{\beta_t^R(k) = \frac{\Xi_{t-1}(k)}{2\lambda_t(k)} = \frac{\sigma_z}{\sigma_c}\cdot\frac{\Xi_{t-1}(k)}{\sqrt{(a^P)^2 + 2\xi_0\,\Xi_{t-1}(k) - \Xi_{t-1}(k)^2}}}, \tag{D.27}$$

$$\boxed{\beta_t^P(k) = \frac{a^P}{2\lambda_t(k)} = \frac{\sigma_z}{\sigma_c}\cdot\frac{a^P}{\sqrt{(a^P)^2 + 2\xi_0\,\Xi_{t-1}(k) - \Xi_{t-1}(k)^2}}}. \tag{D.28}$$

Step 5: Equilibrium existence Define

$$g(\Xi) := (a^P)^2 + 2\xi_0\Xi - \Xi^2. \tag{D.29}$$

The linear equilibrium coefficients are real-valued iff $g(\Xi_{t-1}(k)) > 0$.

Lemma 1 (Existence for all k under $H < a^P$): *Suppose $0 < L < H < a^P < 1$ and $\Xi_{t-1}(k) \in [L, H]$ for all k. Then $g(\Xi_{t-1}(k)) > 0$ for all k, so the linear equilibrium exists for every realized k.*

Proof. Since $\xi_0 > 0$ and $\Xi > 0$ on the relevant domain, we have

$$g(\Xi) = (a^P)^2 + 2\xi_0\Xi - \Xi^2 > (a^P)^2 - \Xi^2.$$

For any $\Xi \in [L, H]$, we have $\Xi \le H < a^P$, so $(a^P)^2 - \Xi^2 \ge (a^P)^2 - H^2 > 0$. Therefore $g(\Xi) > 0$ for all $\Xi \in [L, H]$. ■

F. Propositions

Fix k and use the equilibrium coefficients. Conditional on (θ_t^R, k), objective expected profit is

$$\begin{aligned}\mathbb{E}[\pi_t^R \mid \theta_t^R, k] &= \mathbb{E}\big[x_t^R(v_t^R + v_t^P - \lambda_t(k)\omega_t) \,\big|\, \theta_t^R, k\big] \\ &= x_t^R \left(\mathbb{E}[v_t^R \mid \theta_t^R] - \lambda_t(k)\mathbb{E}[\omega_t \mid \theta_t^R, k]\right), \end{aligned} \tag{D.30}$$

because $\mathbb{E}[v_t^P \mid \theta_t^R] = 0$ and $\mathbb{E}[x_t^P + z_t \mid \theta_t^R, k] = 0$. Moreover, $\mathbb{E}[v_t^R \mid \theta_t^R] = \xi_0\theta_t^R$ by the same self-normalization logic, and $\mathbb{E}[\omega_t \mid \theta_t^R, k] = x_t^R$. Thus, with $x_t^R = \beta_t^R(k)\theta_t^R$,

$$\mathbb{E}[\pi_t^R \mid \theta_t^R, k] = \beta_t^R(k)(\theta_t^R)^2\Big(\xi_0 - \lambda_t(k)\beta_t^R(k)\Big). \tag{D.31}$$

Using $\lambda_t(k)\beta_t^R(k) = \Xi_{t-1}(k)/2$ (from (D.17)), we obtain the sign condition

$$\boxed{\mathbb{E}[\pi_t^R \mid \theta_t^R, k] < 0 \iff \Xi_{t-1}(k) > 2\xi_0}. \tag{D.32}$$

Integrating over θ_t^R conditional on k yields a closed form:

$$\mathbb{E}[\pi_t^R \mid k] = \frac{\sigma_c\sigma_z}{2} \cdot \frac{\Xi_{t-1}(k)\big(2\xi_0 - \Xi_{t-1}(k)\big)}{\sqrt{(a^P)^2 + 2\xi_0\,\Xi_{t-1}(k) - \Xi_{t-1}(k)^2}}. \tag{D.33}$$

Two lemmas: monotonicity in k and in perceived ability

Lemma 2 (Perceived ability increases in k): *For fixed t, the mapping $k \mapsto \Xi_{t-1}(k)$ is strictly increasing.*

Proof. From (D.12), $\Xi_{t-1}(k) = L + (H - L)\psi_{t-1}(k)$, so it suffices to show $\psi_{t-1}(k)$ increases in k. The odds ratio is

$$\frac{\psi_{t-1}(k)}{1 - \psi_{t-1}(k)} = \frac{\phi_0}{1 - \phi_0}\left(\frac{H}{L}\right)^k \left(\frac{1 - H}{1 - L}\right)^{t-1-k},$$

which is strictly increasing in k because $H/L > 1$ and $(1 - H)/(1 - L) < 1$. ■

Lemma 3 (Aggressiveness increases in perceived ability): *Holding $(\xi_0, a^P, \sigma_c, \sigma_z)$ fixed and restricting to the existence region $g(\Xi) > 0$, the mapping*

$$\Xi \;\mapsto\; \beta^R(\Xi) = \frac{\sigma_z}{\sigma_c}\frac{\Xi}{\sqrt{g(\Xi)}}$$

is strictly increasing for $\Xi > 0$.

Proof. Differentiate:

$$\frac{d}{d\Xi}\left(\frac{\Xi}{\sqrt{g(\Xi)}}\right) = \frac{g(\Xi) - \frac{\Xi}{2}g'(\Xi)}{g(\Xi)^{3/2}}, \qquad g'(\Xi) = 2\xi_0 - 2\Xi.$$

Compute the numerator:

$$g(\Xi) - \frac{\Xi}{2}g'(\Xi) = \left((a^P)^2 + 2\xi_0\Xi - \Xi^2\right) - \Xi(\xi_0 - \Xi) = (a^P)^2 + \xi_0\Xi > 0.$$

Since $g(\Xi) > 0$ in equilibrium, the derivative is strictly positive. ■

Proposition 1 (Confidence increases in χ). *Fix t. Under the binomial shortcut $K_{t-1} \sim \text{Binomial}(t-1, \chi)$, The Retail Investor's perceived signal quality $\Xi_{t-1}(K_{t-1})$ is increasing in χ in the first-order stochastic dominance sense (and hence in expectation).*

Proof. K_{t-1} is increasing in χ in the FOSD sense for the binomial family. By the previous lemma, $\Xi_{t-1}(k)$ is strictly increasing in k. Composition preserves FOSD monotonicity. ■

Proposition 2 (Trading aggressiveness increases in χ). *Fix t. On the equilibrium existence region, the equilibrium trading aggressiveness $|\beta_t^R(K_{t-1})|$ is increasing in χ (FOSD and in expectation).*

Proof. By the closed form (D.27), $\beta_t^R(k) = \beta^R(\Xi_{t-1}(k))$ where $\beta^R(\cdot)$ is strictly increasing in Ξ (Lemma above) and $\Xi_{t-1}(k)$ is strictly increasing in k. Therefore $\beta_t^R(k)$ is increasing in k, and since K_{t-1} increases in χ in the FOSD sense, $\beta_t^R(K_{t-1})$ increases in χ. ■

Lemma 4 (Profit is hump-shaped in perceived ability): *Fix $(\xi_0, a^P, \sigma_c, \sigma_z)$ and define $F(\Xi)$ as the conditional expected profit factor*

$$F(\Xi) := \frac{\Xi(2\xi_0 - \Xi)}{\sqrt{(a^P)^2 + 2\xi_0\Xi - \Xi^2}} \quad \textit{on the region } g(\Xi) > 0.$$

Then $F(\Xi)$ is strictly increasing on $(0, \xi_0)$ and strictly decreasing on (ξ_0, ∞) (intersected with $g(\Xi) > 0$).

Proof. Differentiate $F(\Xi)$. A direct calculation yields

$$F'(\Xi) = -(\Xi - \xi_0) \cdot \frac{2(a^P)^2 + 2\xi_0\Xi - \Xi^2}{g(\Xi)^{3/2}}.$$

On the existence region $g(\Xi) > 0$, the factor $2(a^P)^2 + 2\xi_0\Xi - \Xi^2$ is strictly positive, so the sign of $F'(\Xi)$ is the opposite of $(\Xi - \xi_0)$. ■

Proposition 3 (Profits decrease in overconfidence; sufficiently overconfident retail investors lose money). *Fix t and condition on a realized k.*

a. *(Falling profits as overconfidence grows.) The Retail Investor's objective expected profit $\mathbb{E}[\pi_t^R \mid k]$ is strictly decreasing in $\Xi_{t-1}(k)$ whenever $\Xi_{t-1}(k) > \xi_0$.*
b. *(Negative profits.) $\mathbb{E}[\pi_t^R \mid \theta_t^R, k] < 0$ if and only if $\Xi_{t-1}(k) > 2\xi_0$.*

Proof. Part (a) follows from (D.33) and the hump-shape lemma: $\mathbb{E}[\pi_t^R \mid k]$ is proportional to $F(\Xi_{t-1}(k))$, which is decreasing for $\Xi_{t-1}(k) > \xi_0$. Part (b) is exactly (D.32).

■

E. Descriptive Statistics for Additional Experiments

Table AI. Descriptive statistics for the subjects of Experiment 2.

	Full sample (N = 602)			*Selling Gains* (N = 318)			*Selling Losses* (N = 284)		
	Mean	Median	St. Dev.	Mean	Median	St. Dev.	Mean	Median	St. Dev.
Female	0.56	1.00	0.50	0.55	1.00	0.50	0.56	1.00	0.50
Age (in years)	45.67	44.00	13.76	46.10	45.00	14.17	45.20	44.00	13.30
Average portfolio performance (in $)	232.53	234.00	13.92	234.03	236.00	13.55	230.86	232.25	14.16
Subject payment (in $)	2.02	2.02	0.18	2.01	2.01	0.17	2.04	2.04	0.18
Risky stock investment (pre)	3.48	4.00	1.63	3.58	4.00	1.63	3.37	3.00	1.62

Table AII. Descriptive statistics for the subjects of Experiment 3.

	Full sample (N = 305)			*Selling Gains* (N = 160)			*Selling Losses* (N = 145)		
	Mean	Median	St. Dev.	Mean	Median	St. Dev.	Mean	Median	St. Dev.
Female	0.51	1.00	0.50	0.49	0.00	0.50	0.53	1.00	0.50
Age (in years)	38.76	37.00	11.34	37.42	36.00	10.59	40.25	39.00	11.99
Average portfolio performance (in $)	225.60	224.00	13.10	222.84	222.50	11.91	228.66	229.00	13.70
Subject payment (in $)	2.94	2.96	0.20	2.91	2.94	0.21	2.98	3.00	0.18

F. 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.

G. Evidence for a Positive Memory Bias

Investors in our sample selectively recall their realized gains and losses, which is in line with previous findings from the lab (Gödker et al., 2025). As depicted in Table AIV, 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 AIII. 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 in 2019 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

Table AIV. 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 in 2019 and the first half of 2020.

N = 415	**Mean**	**St. Dev.**	***t*-statistic**
Recalled # of Realized Gains	4.22	5.34	
Actual # of Realized Gains	2.52	5.03	
Difference (Memory Bias)	1.70	4.09	8.47
Recalled # of Realized Losses	0.82	1.77	
Actual # of Realized Losses	1.32	3.35	
Difference (Memory Bias)	-0.49	3.07	-3.26

Respondents were asked in July 2020 about their number of realized gains and losses in 2019. It is, therefore, possible that some of the recall bias is due to individuals not remembering whether a transaction happened in 2019 or in the first half of 2020. If there were a lot of realized gains in the first half of 2020, the bias towards remembering more realized gains may not be a generic bias, but a bias specific to when the survey question was asked. First, both the recall bias for realized gains is only weakly correlated with individual's realized gains in the first half of 2020 (Spearman's rho of 0.18) and the recall bias for realized losses is only weakly correlated with individual's realized losses in the first half of 2020 (Spearman's rho of

0.00). Second, we document below the same analysis when including realized gains and losses from the first half of 2020. Respondents remain exhibiting a positive memory bias.

H. Robustness of Field Data Analyses

Table AV. 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. *Self-reported Net Gains* is the difference in the self-reported 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 = self-report 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)		
Self-reported 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

I. Correlation between Confidence and Trading Frequency in the Field

Table AVI. Confidence and trading frequency of Dutch retail investors. This table contains the coefficients and robust standard errors (in parentheses) of OLS regressions. The dependent variable is the investors' total number of trades during the period of January 01, 2013 to May 31, 2020. *Elicited Rank* is investors' beliefs about their performance-based percentile rank among other retail investors (between 0 and 100). *Actual 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 = self-report of realizations first and 0 = otherwise). *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) Nr. Transactions	(2) Nr. Transactions
Elicited Rank	0.188**	0.176*
	(0.09)	(0.09)
Actual Rank		0.060
		(0.08)
Order of Elicitation		4.393
		(4.68)
Constant	24.996***	15.738
	(5.09)	(10.31)
N	1,479	1,479
R^2	0.00	0.00

J. Correlation between Realizations and Trading Frequency in the Field

Table AVII. Realizations and trading frequency of Dutch retail investors. This table contains the coefficients and robust standard errors (in parentheses) of OLS regressions. The dependent variable is the investors' total number of trades during the period of January 01, 2013 to May 31, 2020. *Net Gains* is the difference in the number of investors' realized gains and losses in 2019. *Self-reported Net Gains* is the difference in the self-reported number of investors' realized gains and losses in 2019. *Actual 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 = self-report of realizations first and 0 = otherwise). *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) Nr. Transactions	(2) Nr. Transactions	(3) Nr. Transactions	(4) Nr. Transactions
Net Gains	14.000***	14.032***		
	(3.06)	(3.12)		
Self-reported Net Gains			7.891***	7.815***
			(1.54)	(1.54)
Actual Rank		-0.043		0.108
		(0.08)		(0.11)
Order of Elicitation		3.053		-5.997
		(3.99)		(8.69)
Constant	23.132***	20.823***	31.496***	34.854**
	(2.17)	(7.98)	(5.47)	(16.99)
N	1,479	1,479	415	415
R^2	0.31	0.31	0.20	0.20

K. Attrition Information for Experiments

Table AVIII. Sample attrition across experiments

Experiment	Sample stage	Condition	
		Selling Gains	*Selling Losses*
Experiment 1	Starting sample	246	269
	Attrition: failed comprehension checks	79	76
	Attrition: incomplete sessions	28	31
	Final sample	**139**	**162**
Experiment 2	Starting sample	506	536
	Attrition: failed comprehension checks	137	191
	Attrition: incomplete sessions	51	61
	Final sample	**318**	**284**
Experiment 3	Starting sample	281	255
	Attrition: failed comprehension checks	86	81
	Attrition: incomplete sessions	35	29
	Final sample	**160**	**145**

L. Additional Experimental Data Analyses

Table AIX. Beliefs about own ability (Experiment 2). This table contains the coefficients and robust standard errors (in parentheses) of OLS regression. The analyses use the sample of subjects in Experiment 2. 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. *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	16.893***	16.461***	16.444***	16.889***	
	(1.94)	(1.94)	(1.90)	(1.90)	
Portfolio Performance		0.136*	0.113		
		(0.08)	(0.07)		
Female			-9.250***	-9.341***	-7.448***
			(1.88)	(1.88)	(1.87)
Individual Skill				0.180	
				(0.14)	
Belief High Types Selected					2.531***
					(0.26)
Constant	44.060***	12.574	23.236	45.843***	38.906***
	(1.44)	(17.90)	(17.58)	(3.36)	(2.51)
N	602	602	602	602	602
R^2	0.11	0.12	0.15	0.15	0.17

Table AX. Beliefs about own ability (Experiment 3). This table contains the coefficients and robust standard errors (in parentheses) of OLS regression. The analyses use the sample of subjects in Experiment 3. 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. *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	18.40***	18.13***	17.15***	17.43***	
	(2.71)	(2.78)	(2.78)	(2.73)	
Portfolio Performance		-0.046	-0.033		
		(0.11)	(0.11)		
Female			-3.389	-3.465	-4.448*
			(2.70)	(2.73)	(2.66)
Individual Skill				-0.080	
				(0.18)	
Belief High Types Selected					2.229***
					(0.33)
Constant	42.94***	53.35**	53.11**	47.02***	38.59***
	(2.11)	(25.15)	(25.19)	(4.44)	(3.39)
N	305	305	299	299	299
R^2	0.13	0.13	0.13	0.13	0.14

Table AXI. Beliefs about own ability (pooling Experiment 1, Experiment 2, and Experiment 3. This table contains the coefficients and robust standard errors (in parentheses) of OLS regression. The analyses use the sample of subjects in Experiment 1, 2, and 3. 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. *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	15.974***	15.925***	15.466***	15.494***	
	(1.37)	(1.37)	(1.36)	(1.36)	
Portfolio Performance		0.029	0.024		
		(0.04)	(0.04)		
Female			-7.499***	-7.414***	-6.952***
			(1.36)	(1.36)	(1.32)
Individual Skill				0.101	
				(0.10)	
Belief High Types Selected					2.491***
					(0.17)
Constant	44.702***	38.342***	43.894***	47.144***	38.575***
	(1.03)	(8.11)	(8.11)	(2.43)	(1.73)
N	1,208	1,208	1,202	1,202	1,202
R^2	0.10	0.10	0.12	0.12	0.17

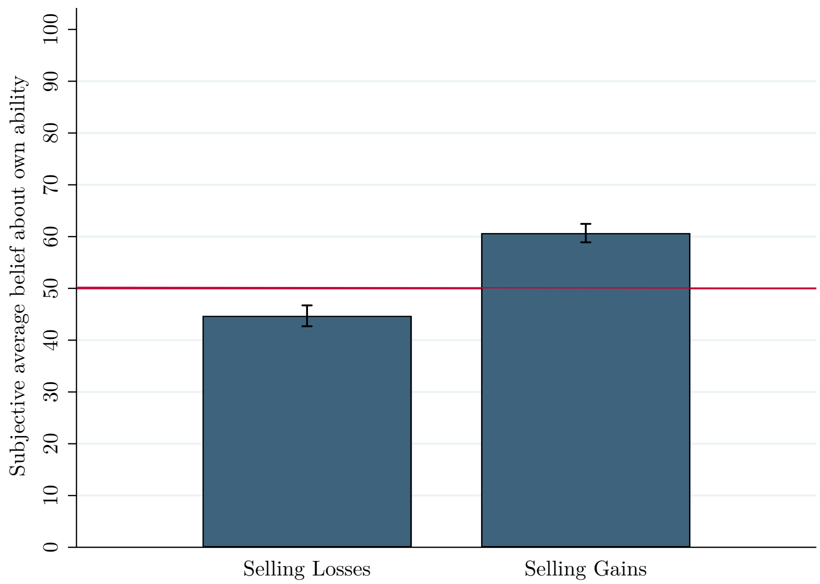


Figure AI. Average beliefs about own ability (pooling Experiment 1, Experiment 2, and Experiment 3). This figure displays mean values of subjects' belief about own ability measured by subjects' elicited likelihood in percent of being ranked in the upper half of a group of 10 participants based on performance in the task (from 0% to 100%). The analyses use the sample of subjects in Experiment 1, 2, and 3. 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%).

Table AXII. Beliefs about number of selected high-type stocks (Experiment 3). This table contains the coefficients and robust standard errors (in parentheses) of OLS regression. The analyses use the sample of subjects in Experiment 3. 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. *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	2.287***	2.400***	2.403***	2.387***
	(0.45)	(0.46)	(0.46)	(0.47)
Portfolio Performance		0.019	0.020	0.027
		(0.02)	(0.02)	(0.02)
Actual High Types Selected			-0.004	-0.031
			(0.12)	(0.12)
Female				0.315
				(0.47)
Constant	6.269***	1.834	1.828	0.218
	(0.31)	(3.96)	(3.99)	(4.17)
N	305	305	305	299
R^2	0.08	0.08	0.08	0.08