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Disposed to Be Overconfident

Abstract

We show that the disposition effect–the tendency of investors to hold losers and sell winners–can be a source of overconfidence. We find experimental evidence that individuals update beliefs about their own investment ability based on realized gains and losses rather than the overall performance of their portfolio. We also find supporting field evidence. Dutch retail investors who realized more gains than losses believe they have higher portfolio performance relative to other investors, even after controlling for their actual portfolio performance. We develop a formal model demonstrating how the disposition effect leads to overconfidence and examine model implications for investors' trading behavior and expected profit.

JEL-Codes: D010, G400.

Keywords: investor beliefs, disposition effect, overconfidence, experimental finance.

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I. Introduction

Most investors tend to sell winners and hold onto losers (Shefrin and Statman, 1985; Odean, 1998a; Weber and Camerer, 1998; Frazzini, 2006). This tendency is called the disposition effect and has been documented for investors across different countries and for a variety of asset classes.[1] Many investors are also overconfident. They systematically believe that their own investment ability is better than it actually is. In theoretical settings, experimental markets, and actual markets, overconfident investors trade more than is in their own best interest and contribute to price volatility (Odean, 1998b; Deaves, Lüders, and Luo, 2009; Barber and Odean, 2001). Although both the disposition effect and investor overconfidence are well-documented phenomena, the interaction between the two remains largely unexplored.

The main contribution of this paper is to show that the disposition effect, a well-documented pattern in investor selling behavior, is a source of investor overconfidence. We identify a biased learning process through which the disposition effect influences investor confidence. The intuition is as follows. Investors vary in ability and often assess their abilities by observing their investment outcomes. While an econometrician might assess an investor's ability by calculating the investor's portfolio return and regressing it on a set of factors, we hypothesize that many real-world investors learn about their own abilities simply by counting how many of their investments were successes and how many were failures. We further hypothesize that investors focus more on realized gains and losses rather than paper (i.e., unrealized) gains and losses when counting successes and failures. Investors exhibiting the disposition effect realize many of their gains and hold onto losing positions. This upwardly biases the proportion of positions sold for a gain and thus leads investors to overestimate their abilities. We support our hypothesis with results from an experiment, field data from Dutch retail investors, and a theoretical model.

In our experiment, subjects participate in an investment task. At the beginning of the first investment period, subjects choose an initial portfolio of five 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 are able to make inferences from previous 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. 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 the period, stock prices change stochastially. Thus subjects hold five stocks in their portfolio

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

throughout the task which ends at the end of five investment periods.

We test for the effect of gain or loss realizations on subjects' beliefs about their ability to choose high-type stocks. To do so, we exogenously manipulate whether subjects sell for a gain or loss. By exogenously imposing sales, we avoid the possibility that an unobserved psychological mechanism is both driving the decisions to realize gains or losses and subjects' confidence in their ability.[2] 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.[3] We randomly assign subjects to one of these two conditions. For stocks in their portfolio, subjects observe both realized gains and losses as well as paper gains and losses each period. At the end of the final period, we measure subjects' self-reported confidence in their ability to select the high-type stocks.

The experiment has three main findings. First, after investing, subjects in the *Selling Gains* condition are significantly more confident in their ability compared to those in the *Selling Losses* condition, although the average number of high-type stocks selected as well as the average portfolio performance do not vary across the two conditions.[4] Second, subjects follow a biased learning process. They form beliefs about their investment ability based on their realized gains and losses but not based on their actual total portfolio performance. Thus they ignore (or underweight) their paper gains and losses when forming beliefs about their ability. Third, gain realizations lead to *over*confidence. On average, subjects in the *Selling Gains* condition report relative ability significantly above the 50th percentile and believe that they have selected significantly more high-type stocks than they actually did.

Our field evidence is based on portfolio and trades data from retail investors at a Dutch financial institution as well as a survey conducted among these retail investors. We show that investors who realize more gains than losses believe they have higher portfolio performance relative to other investors, even after controlling for actual annual portfolio performance.

To formalize the investors' biased learning process and its implications, we develop a theoretical model. In line with our empirical results, the model makes the critical assumption that investors form their beliefs about their investment ability by counting the number of gains and losses they have realized. The model considers two types of investors: a high ability investor whose ability to choose stocks is high, and a low ability investor whose ability to choose stocks is low. Investors vary in their disposition effect. The model produces three predictions. First, investor overconfidence increases with their disposition effect: investors

[2]For example, the desire to have a positive self image could lead investors to sell winners because doing so is in some way consistent with their self-image of a good investor and it could also cause them to self-report higher investment ability.

[3]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.

[4]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, $p = 0.873$). Subjects' profit from the investment task was similar across treatments (T-test, $p = 0.957$).

who are more likely to realize gains than losses overestimate their abilities to choose stocks. This result is consistent with the findings from our experiment and field evidence. Second, the dynamics of investor overconfidence depend strongly on the investor's type. Low-ability investors who exhibit a disposition effect tend to become more overconfident, that is their subjective expectation about their ability increases over time, though the true expectation about their ability decreases. Third, investor overconfidence, generated by the disposition effect, gives rises to both excessive trading and low trading profits.

Most studies in financial economics treat investor overconfidence as a static personal trait and do not examine the processes through which investors become more—or less—overconfident. Economics literature on motivated reasoning investigates overconfidence in a more dynamic way. Several papers argue that people derive utility from overconfidence and other self-serving beliefs (Bénabou and Tirole, 2002; Köszegi, 2006; Brunnermeier and Parker, 2005). Consistent with these studies, recent experimental work provides evidence that people become overconfident by forming and updating optimistic beliefs in ego-relevant domains, such as intelligence (Zimmermann, 2020), beauty (Eil and Rao, 2011), and generosity (Saucet and Villeval, 2019; Di Tella, Perez-Truglia, Babino, and Sigman (2015); Carlson, Maréchal, Oud, Fehr, and Crockett, 2020). In this paper, we explore a learning process that increases investor overconfidence about their ability to invest.

Our study is closely related to the theory of Gervais and Odean (2001), who argue that investors attribute positive portfolio performance to their own ability rather than luck and become overconfident.[5] The innovation of this paper is that we show that investor overconfidence is not only influenced by past performance but by how investors evaluate and *perceive* their past performance. We propose a distinct learning process in which investors assess their ability by counting the number of realized gains and losses. Thus perceived performance can differ substantially from actual performance and separately influence the beliefs investors form about their ability.

We study the link between two common investor biases: the disposition effect and overconfidence. Although many behavioral finance papers focus on a single bias, biases can interact in ways that magnify or offset their influence on behavior (Barberis and Thaler, 2003; Benjamin, 2019).[6] We document a clear causal effect of one bias, the disposition effect, a well-documented pattern in investor selling behavior, on another bias, overconfidence. Overconfidence is a psychological bias that can lead to investor behaviors such as excessive trading and excessive risk taking.

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 af-

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

[6] 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 (2019) study the interaction between individuals' selection neglect and overconfidence.

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

Several studies suggest that investors derive utility from the act of realizing gains and losses on assets that they own (Shefrin and Statman, 1985; Barberis and Xiong, 2012). Frydman, Barberis, Camerer, Bossaerts, and Rangel (2014) find neurological activity consistent with realization utility in an investment like setting. We add new insights to this work by testing consequences of gain and loss realizations for subsequent investor beliefs and learning. This points to a novel connection between realization utility and overconfidence.

More broadly, 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; Du, Niessen-Ruenzi, and Odean, 2022). 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 or preferences channel. Our paper complements this line of research by documenting how realizations compared to paper outcomes affect beliefs. We show that investors' prior gain and loss realizations directly affect their beliefs about their investment ability.

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

II. The Experiment

A. *Experimental Design*

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

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

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

Subjects begin with an endowment of $180 and must buy a portfolio of five stocks from a list of 20 available stocks. The list contains exactly 15 ordinary-type stocks and five high-type stocks, which is known by 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 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 (no additional stock is purchased in period 5). 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.

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

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

We exogenously manipulate whether the computer sells winning stocks or losing stocks from subjects'

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

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

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

Further note, because of the momentum in each stock, selling winner stocks can hurt performance in the long run. In our experiment, we all but eliminate this effect by setting a short time period. In actual markets however, the effect can be substantial. Odean (1998a) estimates that stocks sold by retail investors for a gain outperform stocks they continued to hold for a loss, by 3.4% over the next year. This difference in the returns to realized winners and paper losses is likely driven 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 then measure subjects' beliefs about their anticipated rank in this group. Specifically, we asked subjects to indicate the likelihood that they would be ranked in the upper half of that group (Zimmermann, 2020). Note, 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 the effect on subsequent risk aversion and risk taking, such as the house money effect or the realization effect in risk taking (Thaler and Johnson, 1990; Imas, 2016).

In addition, we elicit subjects' beliefs about how many high-type stocks they selected during the investment task. This measure helps us to shed light on whether our treatments lead people to believe that they selected more or less high-type stocks than they actually did and whether this is a possible mechanism leading to overconfidence about their own 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 for a Bayesian agent. Importantly, across both treatments a Bayesian agent learns from all price increases and decreases – paper gains and losses as well – irrespective of whether a stock sale realized a gain or a loss at a specific point in time.

B. *Procedure, Incentives, and Sample*

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

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

A total of 301 subjects participated in the experiment, 139 subjects in treatment *Selling Gains* and 162 in treatment *Selling Losses*. Participating in the experiment took on average 12 minutes and 42 seconds. The experiment was programmed and conducted with oTree (Chen, Schonger, and Wickens, 2016). This study was pre-registered at AsPredicted under ID 66925. Table I 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, whereas subjects in the *Selling Losses* treatment realized on average 0.98 gains. Subjects' profit from the investment task was similar across treatments (T-test, $p = 0.957$) and subjects selected on average a similar number of high-type stocks across treatments, namely 5.80 in the *Selling Gains* and 5.76 in the *Selling Losses* treatment (T-test, $p = 0.873$) out of 18 stocks they select in total. The average payment was $2.98, which translates to $14 per hour.

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

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

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

C. Results

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

Result 1. *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 II 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

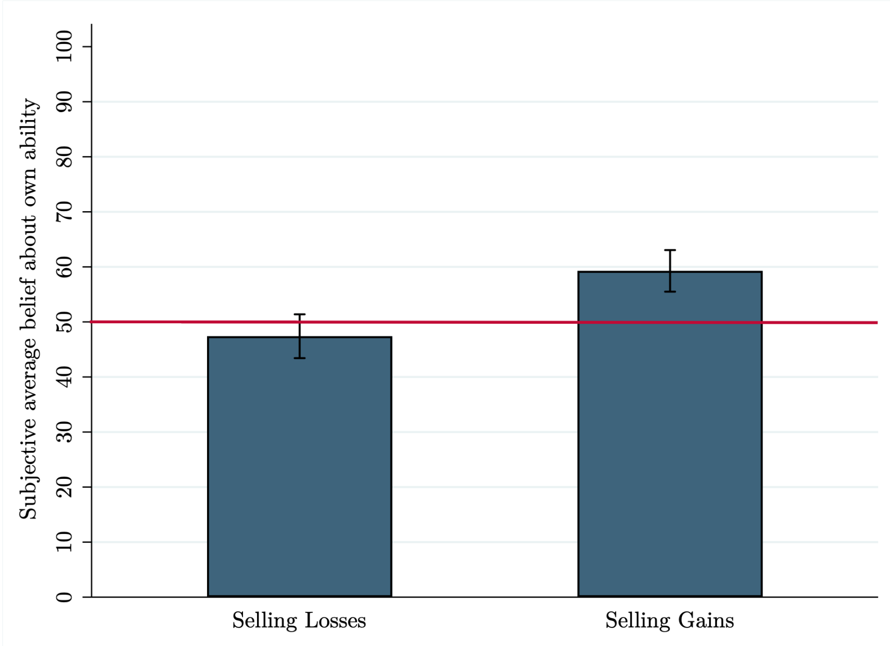


Figure 1. Average beliefs about own ability. This figure displays mean values of subjects' belief about own ability measured by subjects' elicited likelihood in percent of being ranked in the upper half of a group of 10 participants based on performance in the task (from 0% to 100%). The bars represent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

to the *Selling Losses* treatment. Note that in the *Selling Gains* treatment, subjects sold on average 7.74 stocks for a gain, whereas subjects in the *Selling Losses* treatment sold on average 0.96 stocks for a gain. However, the number of gains a subject actually realized varies within treatment. Column 2 reports the result of a regression analysis with the actual number of gains a subject has realized as explanatory variable. The coefficient is significantly positive, confirming the finding from column 1.

Result 2. *Subjects form beliefs about their own ability to invest based on realized gains and losses rather than overall portfolio performance.*

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

Column 3 of Table II 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

Table II. Beliefs about own ability. This table contains the coefficient and robust standard error (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. *Realized Gains* is the number of gains a subject has realized during the task. *Portfolio Performance* is subjects' average portfolio performance of both investment trials, including paper gains and losses and the cash position and excluding initial endowment. *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
Treatment	11.872***		11.889***	
	(2.79)		(2.79)	
# of Realized Gains		1.671***		
		(0.40)		
Portfolio Performance			0.194	
			(0.13)	
Belief # of High Types Selected				2.710***
				(0.33)
Constant	47.401***	46.035***	43.904***	33.084***
	(2.02)	(2.31)	(3.12)	(2.81)
N	301	301	301	301
R^2	0.06	0.05	0.06	0.18

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 3. *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. 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. T-test statistics confirm that subjects' mean belief is significantly different from and larger than 50% (T-test, $p = 0.000$).

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

We find that subjects' confidence in own ability is positively correlated with their reports of how many high-type stocks they believe they have selected. Column 4 of Table II 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 III. Beliefs about number of selected high-type stocks. This table contains the coefficient and robust standard error (in parentheses) of OLS regression. The dependent variable is subjects' reported number of high-type stocks selected (from 0 to 18). *Treatment* is a dummy variable representing our treatment with 1 = Selling Gains and 0 = Selling Losses. *Portfolio Performance* is subjects' average portfolio performance of both investment trials, including paper gains and losses and the cash position and excluding initial endowment. *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) Belief # of High Types Selected	(2) Belief # of High Types Selected
Treatment	0.956**	0.958**
	(0.45)	(0.45)
Portfolio Performance		0.029
		(0.02)
Constant	6.864***	6.348***
	(0.31)	(0.48)
N	301	301
R^2	0.01	0.02

Further, we investigate whether our treatment leads people to believe that they have selected more or less high-type stocks. Table III 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.

Moreover, column 2 of Table III 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.

Finally, we compare subjects' individual beliefs about how many high-type stocks they selected during the investment task to the number of high-type stocks they actually selected (Table IV). We find that subjects believe they have selected significantly more high-type stocks than they actually did if more gains were realized. Specifically, the number of high-type stocks subjects in the *Selling Gains* believe they have selected is on average 2.02 higher than the actual number of high-type stocks they have selected (T-test, $p = 0.000$).

Table IV. Beliefs about selected high-type stocks: reported vs. actual number. This table reports T-test statistics for subjects' reported number of high-type stocks selected (from 0 to 18) and their actual number of high-type stocks selected during the experiment (from 0 to 18). The sample is restricted to subjects in the *Selling Gains* Treatment.

N = 139	**Mean**	**St. Dev.**
Belief # of High Types Selected	7.82	3.82
Actual # of High Types Selected	5.80	2.11
Difference	2.02	4.47
t = 5.33		
p = 0.000		

D. Robustness of Results

It has been documented 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 that are perceived as masculine, such as finance, men claim more ability than women (Deaux and Farris, 1977; Beyer and Bowden, 1997; Prince, 1993). Our experimental data is in line with this established pattern. In our sample, men's reported confidence in their ability to invest is on average 8.79 percentage points higher than women's 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.

Table V presents results from linear regressions. The table provides coefficients from estimates of subjects' beliefs about their ability across gender. The first two columns present our documented treatment effect from Table II while controlling for actual portfolio performance (column 1) as well as both portfolio performance and gender (column 2). Column 3 documents the treatment effect restricting the sample to male subjects and column 4 provides evidence for the treatment effect restricting the sample to female subjects. Both coefficients of the treatment dummy are significantly positive. Male subjects' average beliefs are 13.94% higher in the *Selling Gains* treatment compared to the *Selling Losses* treatment. Female subjects report on average beliefs that are 8.97% higher in the *Selling Gains* treatment compared to the *Selling Losses* treatment.

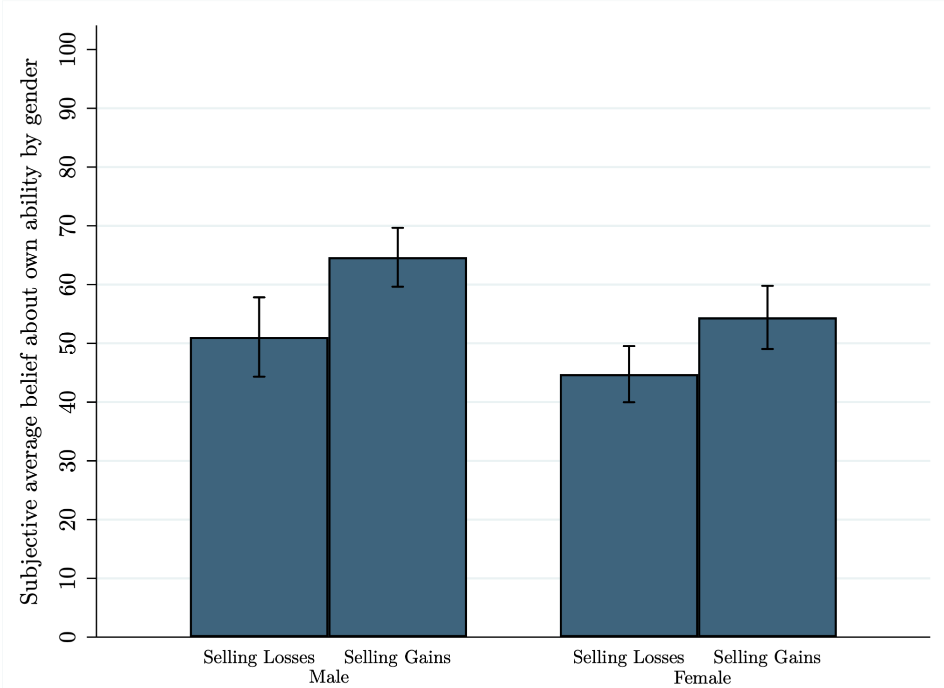


Figure 2. Average beliefs about own ability by gender. This figure displays mean values of subjects' belief about own ability measured by subjects' elicited likelihood in percent of being ranked in the upper half of a group of 10 participants based on performance in the task (from 0% to 100%). The bars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

Table V. Beliefs about own ability by gender. This table contains the coefficient and robust standard error (in parentheses) of OLS regression. The dependent variable is the subjective likelihood in percent of being ranked in the upper half of a group of 10 participants based on performance in the task (from 0% to 100%). *Treatment* is a dummy variable representing our treatment with 1 = Selling Gains and 0 = Selling Losses. *Portfolio Performance* is subjects' average portfolio performance of both investment trials, including paper gains and losses and the cash position and excluding initial endowment. *Female* is a dummy variable representing subject's gender with 1 = Female and 0 = Male. *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) Belief Ability	(2) Belief Ability	(3) Belief Ability (male subjects)	(4) Belief Ability (female subjects)
Treatment	11.889***	11.455***	13.937***	8.965**
	(2.79)	(2.78)	(4.35)	(3.68)
Portfolio Performance	0.194	0.165	0.101	0.274
	(0.13)	(0.13)	(0.18)	(0.18)
Female		-7.836***		
		(2.86)		
Constant	43.904***	48.981***	48.977***	40.364***
	(3.12)	(3.83)	(5.44)	(3.71)
N	301	301	134	167
R^2	0.06	0.09	0.07	0.05

III. Supporting Evidence from the Field

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

A. *Investor Portfolio and Trades Data*

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

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

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

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

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

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

B. *Survey Data*

We conducted an online survey among clients of a Dutch financial institution.[9] The survey was sent out to the financial institution's retail clients aged 18 years or older holding an investment account at the financial institution; excluding very high net worth individuals and those who do not want to be contacted by email. In total, we sent the survey to 120,865 clients. The survey took about 15 minutes to complete and by participating respondents had a chance of winning 300 EUR. In addition, the questionnaire contained incentivized tasks and questions that gave participants the chance of winning extra money, up to an amount of 120 EUR extra. 5,282 clients completed the survey (response rate of 4.4%). The survey was conducted between July 1, 2020 and July 16, 2020. The survey consisted of the following parts: 1) introductory questions for screening, 2) confidence elicitation and elicitation of recalled realizations (in random order), 3) questions about decision-making style and financial knowledge, 4) elicitation of risk perception, 5) questions about demographics. Our analyses use clients' responses to two survey questions as key variables.

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

Investors' recalled realizations. We elicit clients' recollection of their realizations in 2019. We ask survey participants how many stocks they sold for a gain in the year 2019. We explain to participants that "selling for a gain" means selling for a price higher than the average purchase price of that stock. Participants are asked to indicate the number of stocks sold for a gain. Similarly, we ask survey participants how many stocks they sold for a loss in the year 2019. We explain to participants that "selling for a loss" means selling for a price lower than the average purchase price of that stock. Participants are asked to indicate the number

[9] 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.

of stocks sold for a loss. We calculate the difference between the recalled number of realized gains and losses (*Recalled Net Gains*):

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

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

C. Sample Demographics and Summary Statistics

Table VI reports descriptive statistics for our survey participants. We limit our sample to investors who i) responded to the confidence question in the survey and ii) can be linked to portfolio and trade data (1,540 investors). We further exclude observations if the participant's recalled number of realizations deviates by more than +/- 20 from participant's number of total sales in 2019 according to their trading records, which results in a sample of 1,479 retail investors. This investor sample made 8,314 transactions in 2019, i.e., on average each investor made 5.62 trades in 2019. 11% of the sample is female and 89% of the sample is male. On average, survey participants were 55.10 years old (min. 18 years). Our investor sample holds average portfolios of the size of 35,588.52 Euro. The investors earned an average annual portfolio return of 34.70% in 2019. The average elicited percentile rank of investors' portfolio performance in 2019 is 55.70 and the average actual percentile rank is 54.70. Investors realized on average 1.41 gains and 0.53 losses in 2019. The Net Gains are on average 0.88. Investors recall on average to have realized 4.22 gains and 0.82 losses, with recalled Net Gains of 3.40 on average.

D. Results

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

Result 4. *Dutch 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 VII provides coefficients from linear regression estimates of investors' beliefs about their performance-based rank among other retail investors (*Elicited Percentile Rank*). As explanatory variables, the models include investors' difference in the number of gains and losses realized (*Net Gains*) as well as their recollection

Table VI. Descriptive statistics for survey participants.

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

of it (*Recalled Net Gains*). We restrict our analysis to investors who at least had one realization in 2019. The results are robust to restricting the sample to investors who at least had two realizations in 2019 (see Appendix C). We control for investors' actual performance-based percentile rank (*Actual Percentile Rank*). In addition we control for the order of elicitation of the two survey measures, i.e., whether participants were first asked to recollect their realized gains and losses and then about their annual portfolio performance relative to other retail investors or in opposite order. In total, 415 of the 1,479 survey participants responded to the recall questions (28.1%).

The results in column 1 show that participants form their beliefs about own performance relative to others based on the number of realized gains versus losses. The coefficient is significantly positive ($p < 0.001$). The more gains rather than losses an investor realized, the higher the investor's confidence measured by the self-reported performance-based percentile rank. This finding holds when controlling for the investor's actual performance-based percentile rank (column 2). Each additional realized gain over a realized loss increases investor's rank belief by 3.6% ($p < 0.05$).

This result is stronger if we test for the effect of investors' recalled difference in realized gains and losses – those gains and losses that stick to investors' minds (column 3 and 4). Controlling for the actual performance-based percentile rank and order of elicitation, each additional recalled gain over a loss increases investors rank belief by 6.25% ($p < 0.001$).

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

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

IV. The Model

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

A. *Model Setup*

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

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

We further assume

$$v_{i,t} \sim \mathcal{N}(0, \sigma_i^2), \quad t \geq 1, \ \forall i, \tag{4}$$

i.i.d. over time and independent across stocks.

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

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

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

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

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

Although the investor has rational prior beliefs about his ability, he develops biased beliefs over time. We first describe the rational beliefs about the investor's ability. We then discuss how the investor's beliefs differ from the rational beliefs. As in Gervais and Odean (2001), let s_t denote the number of times that the investor's information about risky assets was real by the end of the first t periods: we write $s_t = \sum_{u=1}^{t} \delta_{i(u),u}$, where $i(u)$ denotes the asset with which the investor has a signal in period u; $\delta_{i(u),u}$ equals one if $\theta_{i(u),u} = v_{i(u),u}$; and $\delta_{i(u),u}$ equals zero if $\theta_{i(u),u} \neq v_{i(u),u}$. Under rational beliefs, the probability that $a = H$, computed at the beginning of period t, is

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

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

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

The investor deviates from rational beliefs as follows. Rather than using s_t to assess his ability, the investor uses the number of times that stocks are sold at a gain, denoted by k_t, to assess his ability; later we will provide a precise definition of a stock-level gain or loss. Under these biased beliefs, the probability that $a = H$, computed at the beginning of period t, is

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

where the subscript "b" denotes biased beliefs. The investor's expectation about his ability is

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

We now turn to the investor's buying and selling decisions. Selling decisions are exogenously specified. At any time $t < T$, the investor holds $M \ll N$ risky assets in his portfolio. Suppose that M_1 out of M stocks are held at a gain, and that the remaining $M - M_1$ stocks are held at a loss. With probability χ, the investor will randomly sell one of the M_1 stocks resulting in a gain realization; with the remaining probability $1 - \chi$, the investor will randomly sell one of the $M - M_1$ stocks resulting in a loss realization.[10] Intuitively, this probability χ measures the degree of the disposition effect that the investor is subject to. At time T, the investor sells all his stocks.

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

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

As in Kyle (1985), the market maker is risk-neutral and has rational beliefs. At the beginning of period t, he observes s_{t-1}, k_{t-1}, and $\omega_{i,t} = x_{i,t} + z_{i,t}$, which is the total demand from the investor and the liquidity

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

trader for asset i. The market maker then sets a competitive price $p_{i,t}$ for asset i. Notice that, at the beginning of period t, the market maker does not observe the signal $\theta_{i,t}$.

B. Model Solution

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

$$\begin{aligned} p_{i,t}(\omega_{i,t}, s_{t-1}, k_{t-1}) &= D_{i,t-1} + \lambda_{i,t}(s_{t-1}, k_{t-1}) \cdot \omega_{i,t}, \\ x_{i,t}(\theta_{i,t}, s_{t-1}, k_{t-1}) &= \beta_{i,t}(s_{t-1}, k_{t-1}) \cdot \theta_{i,t}, \end{aligned} \tag{10}$$

where $p_{i,t}$ is the price for asset i, $x_{i,t}$ is the investor's demand for asset i, and $\omega_{i,t} = x_{i,t} + z_{i,t}$ is the total demand from the investor and the liquidity trader.

The investor maximizes, over $x_{i,t}$, his biased expectation of the end-of-period-t profit for holding asset i

$$\begin{aligned} \mathbb{E}_b[\pi_{i,t}|\theta_{i,t}, k_{t-1}, x_{i,t}] &= \mathbb{E}_b\left[x_{i,t} \cdot (D_{i,t} - p_{i,t}(\omega_{i,t}, s_{t-1}, k_{t-1}))|\theta_{i,t}, k_{t-1}, x_{i,t}\right] \\ &= x_{i,t} \cdot [D_{i,t-1} + \mathbb{E}_b[v_{i,t}|\theta_{i,t}, k_{t-1}] - \lambda_{i,t}(s_{t-1}, k_{t-1}) \cdot x_{i,t} - D_{i,t-1}]. \end{aligned} \tag{11}$$

As a result,

$$x_{i,t}(\theta_{i,t}, s_{t-1}, k_{t-1}) = \frac{\mathbb{E}_b[v_{i,t}|\theta_{i,t}, k_{t-1}]}{2\lambda_{i,t}(s_{t-1}, k_{t-1})} = \frac{\Xi_{t-1}(k_{t-1})}{2\lambda_{i,t}(s_{t-1}, k_{t-1})} \cdot \theta_{i,t} \equiv \beta_{i,t}(s_{t-1}, k_{t-1}) \cdot \theta_{i,t}. \tag{12}$$

Next, we turn to the market maker. At the beginning of period t, he sets the price for asset i as follows

$$\begin{aligned} p_{i,t} &= D_{i,t-1} + \mathbb{E}[v_{i,t}|\omega_{i,t}, s_{t-1}, k_{t-1}] = D_{i,t-1} + \mathbb{E}\left[\mathbb{E}[v_{i,t}|\omega_{i,t}, s_{t-1}, k_{t-1}, \delta_{i,t}]|\omega_{i,t}, s_{t-1}, k_{t-1}\right] \\ &= D_{i,t-1} + \mathbb{E}\left[\delta_{i,t} \cdot \mathbb{E}[v_{i,t}|(\omega_{i,t} = \beta_{i,t}(s_{t-1}, k_{t-1}) \cdot v_{i,t} + z_{i,t}), s_{t-1}, k_{t-1}]|\omega_{i,t}, s_{t-1}, k_{t-1}\right]. \end{aligned} \tag{13}$$

Note that $v_{i,t}$ and $\omega_{i,t}$ are jointly Normal. As such, we obtain

$$\mathbb{E}[v_{i,t}|(\omega_{i,t} = \beta_{i,t}(s_{t-1}, k_{t-1}) \cdot v_{i,t} + z_{i,t}), s_{t-1}, k_{t-1}] = \frac{\beta_{i,t}(s_{t-1}, k_{t-1})\sigma_i^2}{\beta_{i,t}^2(s_{t-1}, k_{t-1})\sigma_i^2 + \sigma_{i,z}^2}\omega_{i,t}. \tag{14}$$

Substituting (14) into (13) gives

$$p_{i,t} = D_{i,t-1} + \frac{\xi_{t-1}(s_{t-1}) \cdot \beta_{i,t}(s_{t-1}, k_{t-1})\sigma_i^2}{\beta_{i,t}^2(s_{t-1}, k_{t-1})\sigma_i^2 + \sigma_{i,z}^2}\omega_{i,t} \equiv D_{i,t-1} + \lambda_{i,t}(s_{t-1}, k_{t-1}) \cdot \omega_{i,t}. \tag{15}$$

Equations (12) and (15) together imply

$$\begin{aligned}\beta_{i,t}(s_{t-1},k_{t-1}) &\equiv \sqrt{\frac{\sigma_{i,z}^2}{\sigma_i^2}\cdot\frac{\Xi_{t-1}(k_{t-1})}{2\xi_{t-1}(s_{t-1})-\Xi_{t-1}(k_{t-1})}},\\ \lambda_{i,t}(s_{t-1},k_{t-1}) &\equiv \frac{1}{2}\sqrt{\frac{\sigma_i^2}{\sigma_{i,z}^2}\cdot\Xi_{t-1}(k_{t-1})\cdot\left[2\xi_{t-1}(s_{t-1})-\Xi_{t-1}(k_{t-1})\right]}\,.\end{aligned} \tag{16}$$

Equation (16) makes it clear that the existence of equilibrium requires

$$2\xi_{t-1}(s_{t-1}) > \Xi_{t-1}(k_{t-1}). \tag{17}$$

And it is easy to show that

$$2L \geq H \tag{18}$$

is *sufficient* to guarantee (17) and hence the existence of equilibrium.

Finally, we formally define the gain or loss of asset i. When the asset is first purchased, its price is set according to (15). For subsequent periods, the market maker sets the beginning-of-period-t price for asset i as

$$p_{i,t} = D_{i,t-1}. \tag{19}$$

Denote t_0 as the period when the investor purchases asset i. At the beginning of a subsequent period t, $t > t_0$, asset i's gain or loss is defined as follows. If $x_{i,t_0} \geq 0$,

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

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

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

C. Model Implications

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

Specifically, we set $M = 10$, $T = 10$, $L = 0.4$, $H = 0.6$, $\sigma_i = 1$, $\sigma_{i,z} = 1$, and $\phi_0 = 0.5$. With $T = 0$, the economy has eleven dates (date t goes from zero to ten) and ten periods. At date 0, the investor's ability level is drawn: with probability ϕ_0, $a = H$; and with probability $1 - \phi_0$, $a = L$. The investor is then endowed with ten stocks. At each date $1 \leq t \leq 9$, the investor sells one of the ten stocks according to the probability χ described in the previous section; he is endowed with a signal about a new stock; and he decides his share demand for the stock. At date $t = 10$, the investor sells all his stocks.

Investor overconfidence.—We record the investor's overconfidence level at date $t = 9$ (the beginning of the final period, period 10), measured by $\Xi(k) - \xi(s)$. We simulate the above economy for 10,000 times. We compute the level of overconfidence averaged across the 10,000 investors and then plot it against probability χ, our measure of the disposition effect. Figure 3 below presents this result.

[Place Figure 3 about here]

Figure 3 shows that investor overconfidence increases with χ. Moreover, when χ is low, $\xi(s)$ tends to be greater than $\Xi(k)$ and hence investors exhibit underconfidence. When χ is high, $\xi(s)$ tends to be lower than $\Xi(k)$ and hence investors exhibit overconfidence.

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

[Place Figure 4 about here]

Next, we examine how investor overconfidence varies over time. For this exercise, we set $T = 21$ so the economy has 22 dates (date t goes from zero to 21) and 21 periods. We set $\chi = 1$, so investors always sell stocks at a gain (so long as there is at least one stock in the portfolio that is held at a gain). Figure 4 plots, for $1 \leq t \leq 20$, the level of overconfidence averaged across all investors, across the high-type investors, and across the low-type investors. Overall, the level of investor overconfidence increases over time: the increase is particularly significant for the first few periods and then becomes smaller and eventually negligible.

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

Trading behavior—We set $T = 10$ and simulate the economy for 10,000 times. For each simulation, we compute the magnitude of the investor's share demand for the new risky asset at the beginning of the final period (period 10), measured by $|x|$, where x is the share demand from equation (12). We then compute the absolute share demand, $|x|$, averaged across the 10,000 investors and plot the share demand against probability χ. Figure 5 below presents this result.

[Place Figure 5 about here]

Figure 5 shows that the magnitude of the investor's share demand for risky assets increases with χ, our measure of the disposition effect. As seen in Figure 3, for high values of χ, the disposition effect gives rise to investor overconfidence. This, in turn, generates excessive trading ($|x| > |x^R|$).

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

$$\begin{aligned} \mathbb{E}[\pi_{i,t}|\theta_{i,t}, s_{t-1}, k_{t-1}, x_{i,t}] &= x_{i,t} \cdot [\mathbb{E}[v_{i,t}|\theta_{i,t}, s_{t-1}] - \lambda_{i,t}(s_{t-1}, k_{t-1}) \cdot x_{i,t}] \\ &= x_{i,t} \cdot [\xi_{t-1}(s_{t-1}) \cdot \theta_{i,t} - \lambda_{i,t}(s_{t-1}, k_{t-1}) \cdot x_{i,t}] \,. \end{aligned} \tag{22}$$

Figure 6 below plots the expectation of the investor's profit against probability χ.

[Place Figure 6 about here]

Figure 6 shows that the investor's expected profit is hump shaped in χ, our measure of the disposition effect. For low values of χ, the investor's demand is too low to maximize profits and when χ the investor's demand is too high to maximize profits. In our model, the investor is the only market participant with a signal about the future value of a risky asset. Thus the investor's expected profits are positive. The disposition effect, captured by high values of χ, leads to investor overconfidence, which in turn gives rise to excessive trading. In the model, excessive trading is detrimental to the investor's gross profit because such trading reveals too much information to the market maker. In actual markets, excessive trading further reduces net profit because retail investors incur transaction costs t (Barber and Odean, 2000).

V. Conclusion

We provide empirical evidence that the disposition effect, a well-documented pattern in investor selling behavior, can be a source of investor overconfidence. In an experimental study, we identify a biased learning process as the channel through which the disposition effect can influence investor confidence. When assessing own ability to invest, realized gains and losses have a much stronger influence on individuals' beliefs about ability than overall portfolio performance. Controlling for actual performance on the investment task (and for gender) subjects in our *Selling Gains* condition, who realized mainly gains during the task, are more confident in their ability to select high-type stocks than subjects in the *Selling Losses* condition, who realized mainly losses. 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.

We further provide field evidence for investors' biased learning process. We find that investors who realized more gains than losses believe they have higher portfolio performance relative to other retail investors, while controlling for their actual annual portfolio performance.

Building on our empirical results, we develop a theoretical model that formalizes this intuition. In our model, investors assess their trading ability by counting past realized gains and losses and are subject to the disposition effect. We outline the implications of such a model. First, investor overconfidence increases with the degree of the disposition effect the investor exhibits. That is, when the investor tends to realize rather gains than losses, the biased learning process leads them to overestimate their abilities and become overconfident. Second, the dynamics of investor overconfidence depend on the investor's type. Especially low-type investors tend to become more overconfident over time as their expectation about their ability increases with the number of gain realizations, while the rational expectation about their ability decreases over time towards the actual low level. Lastly, investor overconfidence, generated by the disposition effect, gives rises to both excessive trading and low trading profits.

REFERENCES

Barber, Brad, and Terrance Odean, 2001, Boys will be boys: Gender, overconfidence, and common stock investment, *Quarterly Journal of Economics* 116, 261–292.

Barber, Brad M., and Terrance Odean, 2000, Trading is hazardous to your wealth: The common stock investment performance of individual investors, *Journal of Finance* 55, 773–806.

Barberis, Nicholas, and Richard Thaler, 2003, A survey of behavioral finance, in George Constantinides, Milton Harris, and René M. Stulz, eds., *Handbook of the Economics of Finance* (North Holland, Amsterdam).

Barberis, Nicholas, and Wei Xiong, 2012, Realization utility, *Journal of Financial Economics* 104, 251–271.

Barron, Kai, Steffen Huck, and Philippe Jehiel, 2019, Everyday econometricians: Selection neglect and overoptimism when learning from others, Technical report, WZB Discussion Paper.

Bénabou, Roland, and Jean Tirole, 2002, Self-confidence and personal motivation, *The Quarterly Journal of Economics* 117, 871–915.

Benjamin, Daniel J., 2019, Errors in probabilistic reasoning and judgment biases, in Douglas Bernheim, Stefano DellaVigna, and David Laibson, eds., *Handbook of Behavioral Economics*, 69–186 (North Holland, Amsterdam).

Beyer, Sylvia, and Edward M. Bowden, 1997, Gender differences in self-perceptions: Convergent evidence from three measures of accuracy and bias, *Personality and Social Psychology Bulletin* 23, 157–172.

Brunnermeier, Markus K., and Jonathan A. Parker, 2005, Optimal expectations, *American Economic Review* 95, 1092–1118.

Calvet, Laurent E., John Y. Campbell, and Paolo Sodini, 2009, Fight or flight? portfolio rebalancing by individual investors, *Quarterly Journal of Economics* 124, 301–348.

Campbell, John Y., Tarun Ramadorai, and Benjamin Ranish, 2014, Getting better or feeling better? how equity investors respond to investment experience, NBER working paper No. 20000.

Carlson, Ryan W., Michel André Maréchal, Bastiaan Oud, Ernst Fehr, and Molly J. Crockett, 2020, Motivated misremembering of selfish decisions, *Nature Communications* 11, 2100.

Chen, Daniel L., Martin Schonger, and Chris Wickens, 2016, otree - an open-source platform for laboratory, online, and field experiments, *Journal of Behavioral and Experimental Finance* 9, 88–97.

Choi, James J., David Laibson, Brigitte C. Madrian, and Andrew Metrick, 2009, Reinforcement learning and savings behavior, *Journal of Finance* 64, 2515–2534.

Deaux, Kay, and Elizabeth Farris, 1977, Attributing causes for one's own performance: The effects of sex, norms, and outcome, *Journal of research in Personality* 11, 59–72.

Deaves, Richard, Erik Lüders, and Guo Ying Luo, 2009, An experimental test of the impact of overconfidence and gender on trading activity, *Review of Finance* 13, 555–575.

Di Tella, Rafael, Ricardo Perez-Truglia, Andres Babino, and Mariano Sigman, 2015, Conveniently upset: Avoiding altruism by distorting beliefs about others' altruism, *American Economic Review* 105, 3416–3442.

Du, Mengqiao, Alexandra Niessen-Ruenzi, and Terrance Odean, 2022, Stock repurchasing bias of mutual funds, Working paper, University of Mannheim and University of California, Berkeley.

Eil, David, and Justin M. Rao, 2011, The good news-bad news effect: Asymmetric processing of objective information about yourself, *American Economic Journal: Microecenomics* 3, 114–138.

Feng, Lei, and Mark S. Seasholes, 2005, Do investor sophistication and trading experience eliminate behavioral biases in financial markets?, *Review of Finance* 9, 305–351.

Fischbacher, Urs, Gerson Hoffmann, and Simeon Schudy, 2017, The causal effect of stop-loss and take-gain orders on the disposition effect, *Review of Financial Studies* 30, 2110–2129.

Frazzini, Andrea, 2006, The disposition effect and underreaction to news, *The Journal of Finance* 61, 2017–2046.

Frydman, Cary, Nicholas Barberis, Colin Camerer, Peter Bossaerts, and Antonio Rangel, 2014, Using neural data to test a theory of investor behavior: An application to realization utility, *The Journal of Finance* 69, 907–946.

Frydman, Cary, Samuel M Hartzmark, and David H Solomon, 2018, Rolling mental accounts, *The Review of Financial Studies* 31, 362–397.

Frydman, Cary, and Antonio Rangel, 2014, Debiasing the disposition effect by reducing the saliency of information about a stock's purchase price, *Journal of economic behavior & organization* 107, 541–552.

Genesove, David, and Christopher Mayer, 2001, Loss aversion and seller behavior: Evidence from the housing market, *Quarterly Journal of Economics* 116, 1233–1260.

Gervais, Simon, and Terrance Odean, 2001, Learning to be overconfident, *Review of Financial Studies* 14, 1–27.

Grinblatt, Mark, and Matti Keloharju, 2001, What makes investors trade?, *Journal of Finance* 56, 589–616.

Heath, Chip, Steven Huddart, and Mark Lang, 1999, Psychological factors and stock option exercise, *Quarterly Journal of Economics* 114, 601–627.

Imas, Alex, 2016, The realization effect: Risk-taking after realized versus paper losses, *American Economic Review* 106, 2086–2109.

Jehiel, Philippe, 2018, Investment strategy and selection bias: An equilibrium perspective on overoptimism, *American Economic Review* 108, 1582–97.

Kaustia, Markku, and Samuli Knüpfer, 2008, Do investors overweight personal experience? evidence from ipo subscriptions, *Journal of Finance* 63, 2679–2702.

Köszegi, Botond, 2006, Ego utility, overconfidence, and task choice, *Journal of the European Economic Association* 4, 673–707.

Kyle, Albert S, 1985, Continuous auctions and insider trading, *Econometrica* 1315–1335.

Lundeberg, Mary A., Paul W. Fox, and Judith Punćcohaŕ, 1994, Highly confident but wrong: Gender differences and similarities in confidence judgments., *Journal of Educational Psychology* 86, 114–121.

Malmendier, Ulrike, and Stefan Nagel, 2011, Depression babies: Do macroeconomic experiences affect risk taking?, *Quarterly Journal of Economics* 126, 373–416.

Meyer, Steffen, and Michaela Pagel, 2022, Fully closed: Individual responses to realized gains and losses, *The Journal of Finance* .

Odean, Terrance, 1998a, Are investors reluctant to realize their losses?, *The Journal of Finance* 53, 1775–1798.

Odean, Terrance, 1998b, Volume, volatility, price, and profit when all traders are above average, *Journal of Finance* 53, 1887–1934.

Prince, Melvin, 1993, Women, men, and money styles., *Journal of Economic Psychology* 14, 175–182.

Saucet, Charlotte, and Marie Claire Villeval, 2019, Motivated memory in dictator games, *Games and Economic Behavior* 117, 250–275.

Shapira, Zur, and Itzhak Venezia, 2001, Patterns of behavior of professionally managed and independent investors, *Journal of Banking and Finance* 25, 1573–1587.

Shefrin, Hersh, and Meir Statman, 1985, The disposition to sell winners too early and ride losers too long: Theory and evidence, *The Journal of finance* 40, 777–790.

Strahilevitz, Michal Ann, Terrance Odean, and Brad M. Barber, 2011, Once burned, twice shy: How naive learning, counterfactuals, and regret affect the repurchase of stocks previously sold, *Journal of Marketing Research* 48, S102–S120.

Taylor, Shelley E., and Jonathon D. Brown, 1988, Illusion and well-being: a social psychological perspective on mental health., *Psychological Bulletin* 103, 193–210.

Thaler, Richard, and Eric Johnson, 1990, Gambling with the house money and trying to break even: The effects of prior outcomes on risky choice, *Management Science* 36, 643–660.

Weber, Martin, and Colin Camerer, 1998, The disposition effect in securities trading: An experimental analysis, *Journal of Economic Behavior and Organization* 33, 167–184.

Zimmermann, Florian, 2020, The dynamics of motivated beliefs, *American Economic Review* 110, 337–61.

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.

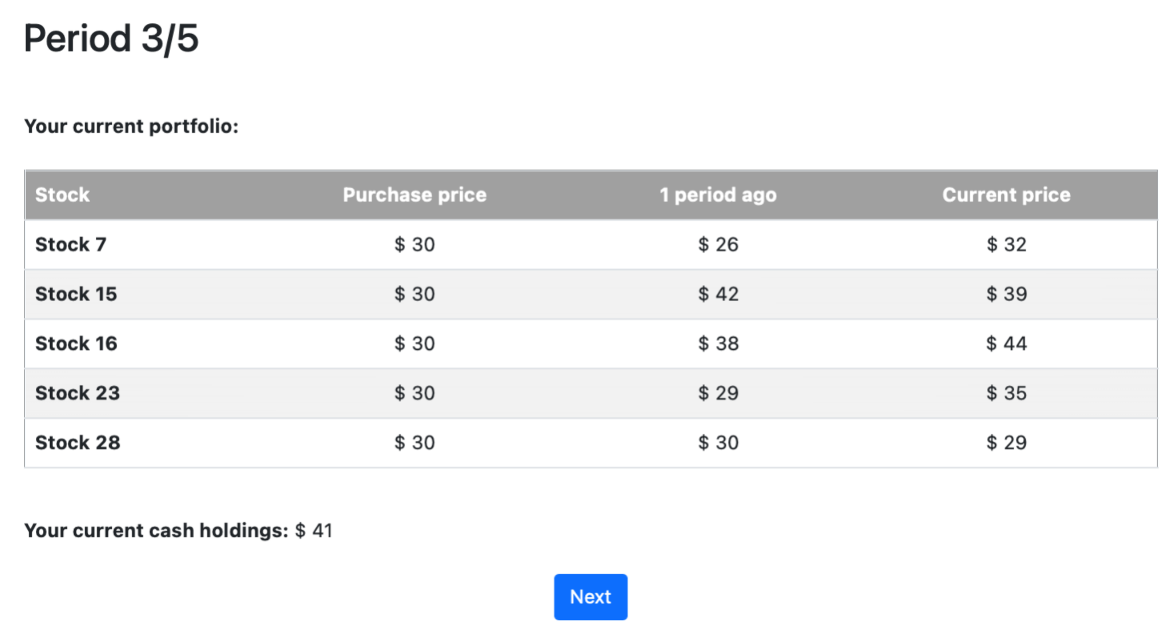
As in period 1, the list contains exactly 3 ordinary-type stocks and exactly 1 high-type stock. You are not told which stock is of which type. However, for each of the 4 stocks, you are shown price changes from the three previous periods.

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. Robustness

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

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

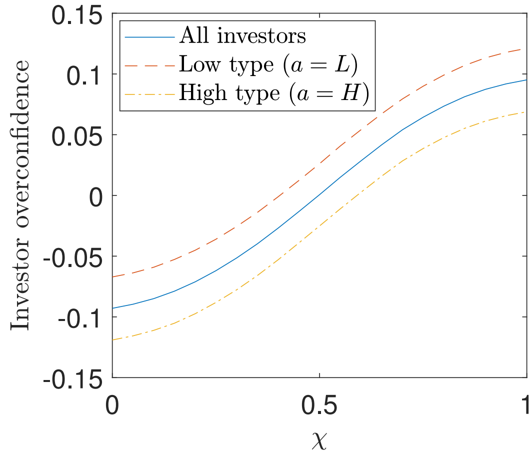


Figure 3. Investor overconfidence as a function of χ. The graph plots the average level of investor overconfidence as a function of probability χ, our measure of the disposition effect. We simulate the economy for 10,000 times. Each time, we simulate the economy for T periods, and at date 0, we draw the investor's ability level: with probability ϕ_0, $a = H$; and with probability $1 - \phi_0$, $a = L$. We record the investor's overconfidence level at the beginning of the final period (period T), measured by $\Xi(k) - \xi(s)$. We then compute the average level of investor overconfidence in three ways: 1) overconfidence averaged across all 10,000 investors; 2) overconfidence averaged across investors of the low type ($a = L$); and 3) overconfidence averaged across investors of the high type ($a = H$). Besides χ, the other parameter values are: $M = 10$, $T = 10$, $L = 0.4$, $H = 0.6$, $\sigma_i = 1$, $\sigma_{i,z} = 1$, and $\phi_0 = 0.5$.

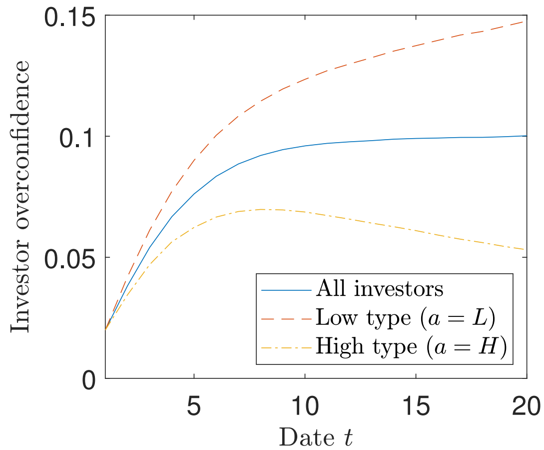


Figure 4. Time evolution of investor overconfidence. The graph plots investor overconfidence as a function of time. We simulate the economy for 10,000 times. Each time, we simulate the economy for T periods, and at date 0, we draw the investor's ability level: with probability ϕ_0, $a = H$; and with probability $1 - \phi_0$, $a = L$. We record the investor's overconfidence level, measured by $\Xi(k) - \xi(s)$, on date $1 \leq t \leq T - 1$. We then compute, for each of these dates, the average level of investor overconfidence in three ways: 1) overconfidence averaged across all 10,000 investors; 2) overconfidence averaged across investors of the low type ($a = L$); and 3) overconfidence averaged across investors of the high type ($a = H$). The parameter values are: $M = 10$, $T = 21$, $L = 0.4$, $H = 0.6$, $\sigma_i = 1$, $\sigma_{i,z} = 1$, $\phi_0 = 0.5$, and $\chi = 1$.

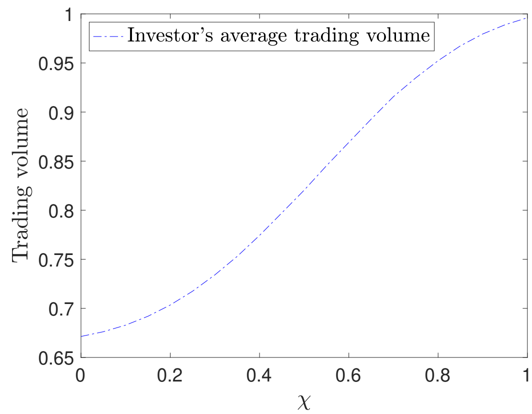


Figure 5. Trading volume as a function of χ. The graph plots the investor's average trading volume, as a function of probability χ, our measure of the disposition effect. We simulate the economy for 10,000 times. Each time, we simulate the economy for T periods, and at date 0, we draw the investor's ability level: with probability ϕ_0, $a = H$; and with probability $1 - \phi_0$, $a = L$. We record the investor's absolute share demand for a risky asset at the beginning of the final period (period T), measured by either $|x|$ (if investors hold subjective expectations) or by $|x^R|$ (if investors hold objective expectations). We then take the average of these absolute share demands across the 10,000 investors. Besides χ, the other parameter values are: $M = 10$, $T = 10$, $L = 0.4$, $H = 0.6$, $\sigma_i = 1$, $\sigma_{i,z} = 1$, and $\phi_0 = 0.5$.

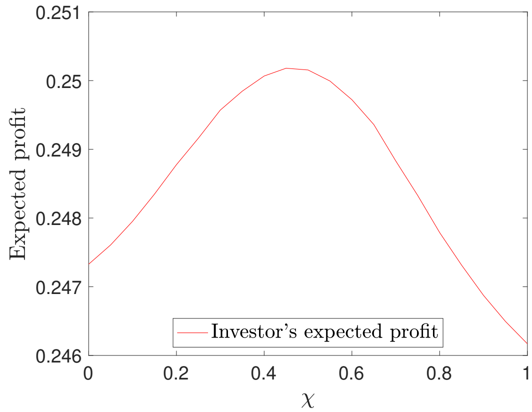


Figure 6. Expected profit as a function of χ. The graph plots the investor's expected profit from the final investment, each against probability χ, our measure of the disposition effect. We simulate the economy for 10,000 times. Each time, we simulate the economy for T periods, and at date 0, we draw the investor's ability level: with probability ϕ_0, $a = H$; and with probability $1 - \phi_0$, $a = L$. We record the objective expectation of the investor's profit from the final investment made at the beginning of the final period (period T). We then take the average of these expected profits across the 10,000 investors. Besides χ, the other parameter values are: $M = 10$, $T = 10$, $L = 0.4$, $H = 0.6$, $\sigma_i = 1$, $\sigma_{i,z} = 1$, and $\phi_0 = 0.5$.