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Attention to Extreme Returns

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Abstract

It has been shown that individual investors are more likely to buy rather than sell stocks that catch their attention. This can lead to suboptimal choices when attention-attracting qualities of a stock may indirectly detract from its utility. This paper tests the causal effect of extreme stock returns on investors' purchase behavior at the individual level by means of a controlled laboratory experiment. We find a strong asymmetry, as shares of stocks with recent extreme negative returns are more likely to be purchased than shares of stocks with recent less extreme negative returns. Yet, comparable patterns are not observed for stocks with positive returns. We further track subjects' eye movements and show that individual visual attention mediates our treatment effect. Interestingly, the results show that attention-driven purchase behavior occurs even in situations in which it reduces subjects' expected return.

JEL Classification: D12, G11, G41
Keywords: Attention, Investor Behavior, Stock Market, Experiments

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1 Introduction

It is part of human nature that some features of the environment attract our attention. Most of the time this is helpful. For example, responding to changes in the environment or the appearance of new stimuli can have survival value. Shifting attention to a car approaching a cross-walk too fast might save us from colliding.

In the context of the stock market, returns might be such an attention-grabbing feature: they are frequently reported and subject to continuous change. Changes in returns are most likely to catch our attention if they are extreme: as an example, returns can be substantially different from returns in previous periods. However, stock returns' attention-grabbing characteristics do not necessarily coincide with the respective stocks' attractiveness as investment. Theory suggests that how individuals allocate attention impacts their economic choice (Bordalo, Gennaioli, and Shleifer, 2012; Schwartzstein, 2014). Indeed, it has been shown that the attention to salient features is an important factor in explaining risky choice (Frydman and Mormann, 2018). This paper investigates whether attention-grabbing characteristics of stock returns guide individuals' attention and thus influence their subsequent investment choice. We investigate both situations in which these attention-grabbing characteristics are positively correlated with stock performance and situations in which these two are negatively correlated.

Building on the notion that investors who want to purchase stocks are likely to focus on stocks that catch their attention, there is robust evidence of a general attention effect in financial markets (Barber and Odean, 2008; Gervais, Kaniel, and Mingelgrin, 2001; Odean, 1999). High levels of investor attention seem to induce buy-sell imbalances as well as abrupt price reactions (Barber and Odean, 2008; Da, Engelberg, and Gao, 2011), whereas limited investor attention appears to cause underreaction to new information (DellaVigna and Pollet, 2009; Huberman and Regev, 2001).

Previous research on investor attention is usually based on empirical analyses of stock market data. The key challenge of this type of analysis is that competing explanations of observed trading behavior are difficult or impossible to disentangle. Imagine a stock with an extreme positive return in the previous period – a proxy for attention that is frequently used (e.g., Barber and Odean (2008)). The observation that investors are net buyers of this stock could be either driven by a belief in stock price momentum, by a preference for stocks with volatile prices, or by the fact that this return pattern catches investors' attention. Now imagine a stock with an extreme negative return in the previous period. The observation that investors are net buyers of this stock might either be related to a belief in the mean reversion of stock prices, by a preference for stocks with high volatility, or to the attention-grabbing characteristics of extreme negative returns. In both examples, investors might rationally trade on their beliefs regarding the future stock price development and risk preferences. Thus, in real-world stock market data, the effects of trading on beliefs, trading on preferences, and trading on attention can hardly be disentangled. As a remedy, some empirical studies resort to an ex-post rationalization of preferences or beliefs, but such measures are unlikely to fully mirror investors' ex-ante preferences and beliefs. In addition, the causal interpretation is ambiguous; as an example, extreme returns could both induce and follow excessive investor attention. Lastly, in many instances, a clear conclusion whether attention-driven investing has the potential to adversely effect individuals' financial position cannot be drawn.

Using natural experiments or settings with information events varying in media coverage, more recent studies establish a causal relation between attention-catching events and investment behavior. These studies show the causal effect of media coverage on local trading, of being positioned at the front page of the Bloomberg terminal news screen on the security's market dynamics, such as trading volume, and of being mentioned in a prominent ranking list on flows into mutual funds (Engelberg and Parsons, 2011; Fedyk, 2019; Kaniel and Parham, 2017). Yet, these studies use events attracting attention in the cross-section, which makes conclusions about the nature and underlying mechanisms of individual attention-driven investment behavior difficult.

This paper enhances the understanding of investor attention by means of an incentivized laboratory experiment. We study the causal effect of extreme stock returns on investors' purchase behavior at the individual level.[1] By providing subjects with lottery-like investment opportunities, we are able to examine risky decision-making in an abstract stock market setting. Importantly, we include a direct measure of visual attention at the individual level by recording subjects' eye movements during their investment tasks using eye tracking devices. In contrast to stock market data, our experimental design allows us to observe individual attention and to separate rational trading on investor preferences and beliefs from attention-driven purchase behavior. While beliefs in momentum or mean reversion and risk preferences might correctly drive attention-like trading patterns observed in stock market data, they can constitute a bias in our experiment by design. Subjects make 10 independent investment decisions based on information about past asset price changes. We manipulate the magnitude of the price change of one given stock in order to vary the attention-grabbing characteristic of this stock's return. In line with Barber and Odean (2008), we vary the stock's return in the period preceding the investment decision by implementing two return

[1]Our experiment focuses on purchase decisions only, since investor attention has been shown to matter most on the buy side where the whole universe of stocks needs to be considered while selling decisions should only consider the assets currently held in a portfolio (Barber and Odean, 2008).

conditions: an extreme return as treatment condition and a normal return condition as control. Importantly, the presented stocks differ in their quality, which can be observed by our subjects when following the concept of Bayesian optimization. As a critical element of our experiment design, the stock quality is constant across the two return conditions (i.e., treatment and control).

We find that attention-grabbing returns affect stock purchase patterns: stocks with extreme prior returns have higher purchase volumes subsequently. However, this finding hides part of the mechanisms behind investor attention. Analyzing our results in more detail, we find evidence for asymmetry in investor attention. While stocks with positive extreme returns do not seem to channel subjects' purchase decisions, stocks with negative extreme returns experience a significantly higher purchase volume compared to the control treatment. Moreover, our analysis of eye tracking data reveals that subjects' visual attention to the respective stock mediates our treatment effect. Extreme returns increase subjects' stock purchase volume through channeling subjects' visual focus on the respective stock. Further, we find that in our experiment, attention-driven purchase behavior occurs even in situations in which it reduces investors' wealth. Subjects show attention-driven stock buying behavior even for stocks with negative *expected* returns. This suggests that attention-driven purchase behavior has the potential to lead to wealth reductions for investors in the stock market. This conclusion is supported by the observation that the demand for stocks with attention-grabbing returns increases at the expense of the demand for stocks with non-attention-grabbing returns, leaving investors' total amount invested in stocks unchanged.

This paper makes several contributions to the existing literature. First, we provide causal evidence on attention-grabbing returns affecting investment patterns in the stock market. The controlled lab environment allows for a clear identification of causal effects – disentangled from alternative determinants such as institutional differences that might affect individuals' investment decisions in the field. Our experimental design provides an environment where the attention-grabbing characteristic of returns is exogenously varied and uncorrelated to stocks' fundamentals. Second, this study enhances our understanding of the nature of investor attention by employing eye tracking devices in the laboratory, allowing us to observe visual attention effects on the individual level. Our results uncover an important attention mechanism, namely asymmetric attention patterns with regard to positive and negative extreme returns. Third, in contrast to archival studies, we are able to identify the true quality of stocks. This allows us to judge whether attention-driven investment behavior increases or decreases investors' return in our experiment.

The remainder of this paper proceeds as follows: In Section 2, we review the related literature. The experiment design is presented in Section 3, along with our hypotheses. The results are presented in Section 4. In Section 5, we discuss the interpretation of our results as evidence of investor attention as well as potential alternative drivers of our results. Potential implications of attention-driven investment behavior in the stock market are investigated in Section 6. Section 7 concludes.

2 Review of Related Literature

Our paper is related to the empirical literature examining the role of investor attention in the stock market. A first strand of this research focuses on the cross-sectional effects of specific attention-grabbing events or salient stock features. Gervais, Kaniel, and Mingelgrin (2001) report that the higher visibility of a stock caused by high trading volume influences the demand and price for that stock. Li and Yu (2012) find that nearness to the 52-week high of the Dow Jones positively predicts future aggregate market returns and that nearness to the historical high negatively predicts market returns. Further, Koester, Lundholm, and Soliman (2016) find that extreme positive earnings surprises attract investor attention by increasing the subsequent number of institutional owners, the number of analysts, and trading volume. More generally, Yuan (2015) reports that market-wide attention events raise the level of attention investors pay to their portfolios, causing them to become more active in processing information and making trading decisions. This is supported by the finding that there is attention co-movement, i.e., investors' firm-specific attention in the stock market correlates with attention to the industry of a firm and the market (Drake, Jennings, Roulstone, and Thornock, 2017). Most closely related to ours is the study by Barber and Odean (2008), who find that investors have a high propensity to purchase attention-grabbing stocks with abnormal trading volume, extreme returns, and high press coverage prior to the investment decision. Disentangling the causal impact of media reporting from the impact of the reported events, Engelberg and Parsons (2011) find a positive impact of local media coverage on local trading.[2]

Building on these findings, a second strand of literature makes use of stock listings and published rankings to identify investor attention. Jacobs and Hillert (2016) find that US stocks near the top of alphabetical listings have higher trading activity and liquidity than stocks near the bottom. Using natural experiments, Fedyk (2019) shows that being positioned at the front page of the Bloomberg terminal news screen affects the security's market dynamics, such as trading volume, and Kaniel and Parham (2017) find a causal effect of being mentioned in a prominent ranking list on flows into mutual funds. Related to these attention effects, Hartzmark (2015) shows that the so-called

[2] Testing the investor recognition hypothesis (Merton, 1987), Fang and Peress (2009) document a related long-term media impact. They show that stocks without media coverage have higher returns than stocks with more media coverage and argue that these results are consistent with limited investor attention.

rank effect – investors' tendency to sell extreme winning and losing positions in their portfolio – determines trading behavior.

A third strand of literature measures investors' attentiveness more directly in the cross-section. Da, Engelberg, and Gao (2011) measure investor attention with Google search frequency and show that attention is related to stock price increases and subsequent reversals as well as to the typical patterns of IPO stocks. Other studies use a company's Wikipedia page views to measure investor attention. Based on this measure, Focke, Ruenzi, and Ungeheuer (forthcoming) document that advertising positively affects investor attention and Brunner and Ungeheuer (2020) finds that stocks classified as daily winners or losers are likely to receive higher attention by investors, while no such effect is observed for stocks with extreme returns but without such classification. So far, only few studies use direct measures of investor attention at the individual level. Using panel data on daily investor online account logins, Karlsson, Loewenstein, and Seppi (2009) and Sicherman, Loewenstein, Seppi, and Utkus (2016) find that investors pay more attention to their portfolios in rising than in flat or falling markets. Investors' logins decrease substantially after market declines and are remarkably low during high volatility periods. Additionally observing what information investors browse and how much time they spend doing it by measuring web-activity, Gargano and Rossi (2018) find that investors pay more attention to large companies that are risky but have high growth potentials.

Our paper is also related to the literature investigating the relation between investor attention and investment performance. Attention-driven investing may affect equilibrium market outcomes as well as individual performance. It is typically argued that attention effects negatively impact stock market performance. Barber and Odean (2008) suggest that if attention and investors' utility are orthogonal or at least negatively correlated, attention-attracting characteristics of an alternative may indirectly detract from its utility. Consequently, attention-based purchase behavior by many investors could temporarily inflate a stock's price, leading to lower subsequent returns. Seasholes and Wu (2007) find that attention-grabbing events coincide with statistically significant mean reversion in prices. Moreover, retail investors' market returns appear to decrease on days following attention-grabbing events (Yuan, 2015).[3] Further, Kumar, Ruenzi, and Ungeheuer (2020) find a significant underperformance of attention-catching stocks – daily winners and losers – after they are bought by retail investors. On the other hand, Gargano and Rossi (2018) provide evidence that investors are more attentive to their brokerage account if it shows better investment performance, both at the portfolio return level and the individual trades level.

[3] A comprehensive overview on the role of investor attention for trading behavior and economic outcomes is provided by Jacobs (2015).

We further relate to theoretical work on investor attention explaining investors' attentional patterns as well as the resulting effects on decision outcomes. Theoretical work by Bordalo, Gennaioli, and Shleifer (2012) models context-dependent choice under risk, which integrates the concept of salience. Salience refers to the disproportionate weighting of information that exhibits higher levels of attention relative to other pieces of information. In an asset market context, the key implication of salience theory is that extreme payoffs receive disproportionate weight in the valuation of assets (Bordalo, Gennaioli, and Shleifer, 2013). Thus, salient returns are overweighted, i.e. exhibit a higher decision weight, compared to non-salient returns. In particular, salient positive features should receive a disproportionate positive decision weight, whereas salient negative features should receive a disproportionate negative decision weight. In contrast, Barber and Odean (2008) argue that assets that attract investors' attention are more likely to be considered and chosen, while assets that do not attract attention might be ignored, i.e. preferences determine choices after attention has determined the choice set.

3 Experimental Design

In this section, we first describe our experimental setup (Section 3.1) along with the treatment (Section 3.2) and then derive our hypotheses (Section 3.3).

3.1 Experimental Setup

Our experimental setting builds on Weber and Camerer (1998). Subjects make individual investment decisions based on information about past asset prices.[4] They have the possibility to purchase shares of risky stocks with different price trends; in contrast to the Weber and Camerer (1998) design, subjects make 10 independent one-shot investment decisions since we do not focus on investment dynamics.[5] Each of the 10 decisions consists of two phases. In the first phase, subjects receive 1,000 experimental currency units (*Taler*) and have the possibility to purchase shares of six stocks with different price trends or alternatively to hold their initial endowment (which does not earn interest).[6] In the following phase, their positions are sold automatically and returns from the

[4] The experiment instructions are provided in Appendix A.

[5] Using independent one-shot decisions has the advantage that path dependencies are unlikely to influence subjects' purchase behavior. As an example, in an experimental setup with interdependent decisions, a subject carrying forward a portfolio from the previous period with high risk might be more likely to invest in stocks with seemingly lower risk.

[6] Offering a risk-free alternative which does not pay any interest is meant to increase the overall level of stock investments and is consistent with Weber and Camerer (1998). Since our main interest lies in the composition of investors' stock portfolios and not in the split between risky and risk-free assets, this design choice does not influence our conclusions.

Table 1: Experimental Design: Control and Treatment

This table displays an exemplary decision task as seen by the control group (left-hand side) and the treated group (right-hand side).

	Control							Treatment						
Period	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**
Price	40	45	48	53	56	46	47	40	45	48	53	56	46	56
Change		(+5)	(+3)	(+5)	(+3)	(-10)	(+1)		(+5)	(+3)	(+5)	(+3)	(-10)	(+10)
Price	45	40	45	46	41	46	41	45	40	45	46	41	46	41
Change		(-5)	(+5)	(+1)	(-5)	(+5)	(-5)		(-5)	(+5)	(+1)	(-5)	(+5)	(-5)
Price	50	49	46	45	35	34	35	50	49	46	45	35	34	35
Change		(-1)	(-3)	(-1)	(-10)	(-1)	(+1)		(-1)	(-3)	(-1)	(-10)	(-1)	(+1)
Price	55	50	53	63	58	53	52	55	50	53	63	58	53	52
Change		(-5)	(+3)	(+10)	(-5)	(-5)	(-1)		(-5)	(+3)	(+10)	(-5)	(-5)	(-1)
Price	60	61	62	63	73	78	77	60	61	62	63	73	78	77
Change		(+1)	(+1)	(+1)	(+10)	(+5)	(-1)		(+1)	(+1)	(+1)	(+10)	(+5)	(-1)
Price	65	75	65	68	73	72	62	65	75	65	68	73	72	62
Change		(+10)	(-10)	(+3)	(+5)	(-1)	(-10)		(+10)	(-10)	(+3)	(+5)	(-1)	(-10)

investment activities are calculated.

The six risky stocks in each decision task have different predefined chances of rising and falling in price. The probability of a price to increase is 65% for one stock type labeled ++, 55% for one stock type labeled +, 50% for two stock types labeled 0, 45% for one stock type labeled −, and 35% for one stock type labeled −−. Notably, prices never remain constant; thus, the chance of a price fall is one minus the chance of rising. The size of the experienced price change is randomly assigned and varies between 1, 3, 5, and 10 Taler. Rises and falls in price are independent across stocks and the probability of a stock's price increase is uncorrelated with the size of the price change; in other words, subjects cannot infer the quality of a stock from the size of the price change.[7] Subjects know the probabilities of price increases and decreases for the different stock types, but do not know which of the stocks offered in each decision task has which chance, since they are neutrally labeled. For each decision, subjects are confronted with completely new stocks, i.e., there is no relation to the stocks from past decisions. To ensure that subjects understand this aspect of the experiment, the labels of the six stocks vary between the decision tasks and no label is used more than once.[8]

Before the experiment, 10 different choice sets with price sequences of six risky stocks each were

[7]We use exactly the same probabilities as in Weber and Camerer (1998). Compared to their setup where the magnitude of price changes is either 1, 3, or 5, we added a more extreme price change of 10. While this choice of parameters does not necessarily imply a positive risk-return relation as assumed by the Capital Asset Pricing Model (CAPM) (Lintner, 1965; Mossin, 1966; Sharpe, 1964), it allows us to separate attention effects generated by extreme returns from alternative purchase motives such as investor preferences or beliefs and fundamental asset values. To ensure that subjects understood the randomness of the magnitude of price changes, i.e., that the magnitude of price changes is unrelated to the stock quality, all subjects had to correctly answer two comprehension questions regarding the magnitude of price changes and the quality of stocks. The questions are provided in Appendix B.

[8]Table 8 in Appendix C displays the labels of the stocks used in the 10 decision tasks.

drawn based on the defined chances of a price increase.[9] In each decision task, subjects are provided with a table containing information about stocks' current prices (Period 0) as well as past prices from six given previous periods (Periods -6 to -1); the left-hand panel of Table 1 shows an example of a decision task (a screenshot of a decision task is displayed in Appendix E). The six stocks have different starting prices. All sessions have the same choice sets.

Using the provided stock information, a fully rational (Bayesian) subject should count the number of times that a stock experienced a price increase in the course of the given periods to infer the stock's chance of a price increase in the next period.[10] Specifically, the stock that has increased most frequently is most likely to be the ++ stock type with the highest chance of a price increase in the next period and subjects should be most likely to buy shares of this stock. With the same logic, the stock with the highest number of price decreases is most likely to be the $--$ stock type and subjects should be least likely to buy shares of this stock. In addition, the $-$ and $--$ stock types have a negative expected return (we refer to them as *negative stocks*), thus buying shares of these stock types reduces subjects' profits on average. Rational investment decisions would only include + and ++ stock types with a positive expected return (we label them *positive stocks*) and potentially 0-drift stocks with an expected return of zero (*neutral stocks*) for reasons of diversification.[11]

Our experiment is incentivized, and subjects' investment decisions during the experiment determine their payout. At the end of each experimental session, one of the 10 decision tasks of each subject is randomly chosen for payout in order to avoid path-dependent decisions. Subjects' Taler holdings are then converted into € based on a known exchange rate of 100 Taler to €1. However, the realized returns of the stocks subjects invested in, namely the difference between buy price and sale price, is doubled.[12] Thus, the payout is computed as shown in Equation (1):

$$T_f = T_s + \sum_{i=1}^{6} 2 \cdot (p_{i,1} \cdot n_{i,1} - p_{i,0} \cdot n_{i,0}) \tag{1}$$

T_f denotes the final amount of Taler, T_s denotes the amount of Taler when a decision task starts (i.e., the initial endowment), $p_{i,t}$ is the price of Stock i in Period t, and $n_{i,t}$ represents the number of shares of Stock i purchased and (automatically) sold in Period t. Subjects' cash holdings are not carried over from one decision to the next. No interest is paid on Taler holdings and subjects do not

[9] The 10 choice sets are depicted in Appendix D.

[10] Since subjects see the full history of stock prices from Period -6 to Period 0 displayed at once, estimates of stock quality are not updated in the proper sense of the word. However, in the following, we refer to Bayesian subjects when subjects behave consistently with Bayesian updating in that they are most likely to purchase shares of stocks with the highest number of price increases.

[11] Diversification is possible since price movements are uncorrelated across stocks in our design.

[12] The range of potential payoffs equals €2 to €18.

face any transaction costs. Short selling and borrowing are not possible.

Subjects have 15 minutes to read the instructions on their own and questions are answered privately. In order to ensure that subjects understand the experimental design, we use introductory comprehension questions that have to be answered correctly before proceeding with the experiment. The investment tasks are followed by a questionnaire with demographic and control questions. Similarly to Dohmen, Falk, Huffman, Sunde, Schupp, and Wagner (2011), subjects are asked to self-assess their risk tolerance in general matters on a scale from 0 (lowest) to 10 (highest); moreover, in order to obtain an objective measure of risk aversion, subjects are asked to complete a lottery task in a multiple price list setting (Holt and Laury, 2002). We also ask for subjects' knowledge in statistics and econometrics.

The experiment was conducted with 117 subjects, mostly business and economics students (about one third of the subjects have no economics or business background), from the experimental laboratory's subject pool. Table 2 displays the summary statistics. Subjects are 24 years old on average; 42% are male. The average self-assessed risk tolerance equals about 5; the average switching point in the multiple price list is almost 6. On average, subjects earned €9.98. For each subject, the experimental session took about 1 hour. Our visual attention analyses are based on a sample of 114 subjects, as the eye-tracking devices of three subjects could not be calibrated sufficiently. The experiment is programmed and conducted with z-Tree (Fischbacher, 2007) and the experimental sessions were organized and administrated with the software hroot (Bock, Baetge, and Nicklisch, 2014).[13]

3.2 Treatment

To study the nature and implications of investor attention, we manipulate the attention-grabbing characteristic of one of the available stocks in each of the 10 decision tasks. In line with Barber and Odean (2008), we vary the stock's return information in the period preceding the investment decision (Period 0) by implementing two return conditions, an extreme return as treatment condition and a normal return condition as control.[14] In our design, we implement price changes by 10 Taler as

[13] As is common practice in laboratory experiments, our subjects are students. On the one hand, compared to the general population our subjects might make smarter investment decisions since many of them study a subject related to business or economics. On the other hand, since all subjects are students they might have lower experience with stock investments and therefore make less appropriate decisions. The net effect of these two drivers is not clear ex-ante.

[14] Previous research has identified further characteristics that coincide with catching investors' attention. As an example, Barber and Odean (2008) additionally investigate news coverage and abnormal trading volume. The latter is also examined by Gervais, Kaniel, and Mingelgrin (2001). Hartzmark (2015) identifies the so-called rank effect as a further driver of trading behavior: traders are more likely to sell extreme winners and extreme losers in their portfolio. As for our experiment, we implement extreme returns.

Table 2: Summary Statistics of Subjects

This table contains the summary statistics of the experimental subjects. *Age* is subjects' age, measured in years; *Male* is a dummy variable which is equal to one if a subject is male; *Business/economics as main field of study* is a dummy variable which is equal to one if a subject studies a major related to business and/or economics; *Advanced statistics knowledge* is a dummy variable which is equal to one if subjects assess their statistics knowledge as advanced (e.g., having completed a statistics class at university); *Risk tolerance* is subjects' self-assessment of their risk tolerance in general matters, measured on a scale from 0 (lowest) to 10 (highest); *HL switching point* is the switching point from the Holt and Laury (2002) lottery task.

	Mean	Median	SD	Min	Max
Age	24.14	24.00	4.80	18.00	53.00
Male	0.42	0.00	0.50	0.00	1.00
Business/economics as main field of study	0.72	1.00	0.45	0.00	1.00
Advanced statistics knowledge	0.57	1.00	0.50	0.00	1.00
Risk tolerance	5.03	5.00	2.27	0.00	10.00
HL switching point	5.76	5.00	1.86	2.00	10.00
N	117				

extreme returns and price changes by 1 Taler as normal returns in the choice sets. As we vary the type of the manipulated stock across the decision tasks, we test choice environments with positive as well as negative stock returns.[15]

For each choice set, we manipulate the magnitude of the price change of *one* given stock. Table 1 displays an example of the manipulation of a positive stock. In the normal return condition (left-hand panel), this stock has a last period return of +1 Taler; in the extreme return condition (right-hand panel), the stock's last period return is +10 Taler. However, we do not manipulate whether the stock experiences a price increase or decrease, which would change the informative value of the price sequence. Importantly, the sequences are chosen such that positive stocks have last-period returns of +1 Taler or +10 Taler in the control and the treatment condition, respectively, and negative stocks have returns of −1 Taler or −10 Taler. As for neutral stocks, one stock has last-period returns of either +1 Taler or +10 Taler while the other has returns of either −1 Taler or −10 Taler. This mechanism implies that manipulated positive stocks have positive normal and extreme returns in the control and the treatment condition, respectively, and manipulated negative stocks have negative normal and extreme returns; it is a critical feature of the experiment design since attention to extreme positive returns can increase utility while attention to extreme negative returns can decrease utility in this setting. One of the positive stocks is manipulated in choice sets 1 to 4, one of the neutral stocks in choice sets 5 and 6, and one of the negative stocks in choice sets 7 to 10. Since the absolute magnitude of a price change (1, 3, 5, or 10 Taler) is randomly assigned to the different stock types, the two conditions do not differ in their informative value for subjects.

[15]Refer to Appendix C for a detailed illustration.

The quality of the manipulated stocks is constant across the treatment and control condition.

This setup allows for a distinction between trading on attention and trading on preferences or beliefs. Since extreme last-period returns are unrelated to stock quality and subjects know this mechanism, trading on extreme last-period returns cannot be explained with investors' beliefs. Moreover, as extreme last-period returns do not change the expected volatility of a stock and subjects know this mechanism, trading on extreme last-period returns cannot be explained with investors' risk preferences.

The experiment follows a between-subjects design. We randomly assign subjects to one of the two return conditions for every decision task; i.e., a given subject might see the control condition of a choice set in one of the 10 decision tasks and the treatment condition of another choice set in another task. In addition, we vary the order of the predefined choice sets between the subjects to prevent order effects. Across the 10 decisions, we also vary the order of the presented stock types and the stocks' initial starting prices (40, 45, 50, 55, 60, and 65 Taler).

In all ten choice sets the information on past stock prices is sufficient to clearly identify the quality of the manipulated stock by counting the number of past price increases and ranking the six stocks accordingly. Consequently, it can be ruled out that a significant treatment effect is caused by subjects not having the possibility to correctly infer the true quality of the manipulated stock.

3.3 Hypotheses

Based on the insights described in Section 2, we expect extreme return patterns in the period preceding the purchase decision – as an attention-grabbing characteristic – to significantly influence subjects' purchase volume of the respective manipulated stock.

Hypothesis 1 *Subjects treated with the extreme return information show a higher purchase volume of the manipulated stock compared to the control group.*

The null hypothesis to Hypothesis 1 is that the purchase volume of manipulated stocks does not differ between the treatment and the control group or that the purchase volume of the manipulated stock is higher for the control group.

Moreover, we are interested in investors' visual focus while making their purchase decisions. As discussed above, eliciting subjects' visual fixations allows us to measure visual attention. Thus, we expect that subjects' visual focus to a stock significantly influences their purchase volume of the respective stock.

Hypothesis 2 *Subjects with higher visual fixation to the information of a stock show a higher purchase volume of the respective stock.*

The null hypothesis to Hypothesis 2 is that subjects' visual fixation is not reflected in subjects' purchase volume of the respective stock or that subjects with higher visual fixation to the information of a stock show a lower purchase volume of the respective stock.

4 Results

This section reports our main results. We first describe subjects' stock buying and portfolio decisions in response to extreme returns implemented in our experiment (Section 4.1). In Section 4.2, we test whether subjects' visual fixations are associated with their stock buying behavior in the experiment.

4.1 Extreme Returns

To investigate Hypothesis H1, we first examine subjects' purchase decisions in response to extreme returns implemented in our experiment.

4.1.1 Attention Effects in Stock Buying Behavior

For the following analyses, we define purchase volume as the number of stock shares purchased.[16] We pool the data from all subjects since all subjects are presented the same price sequences (except for the Period 0 return of the treated stock for a given decision).

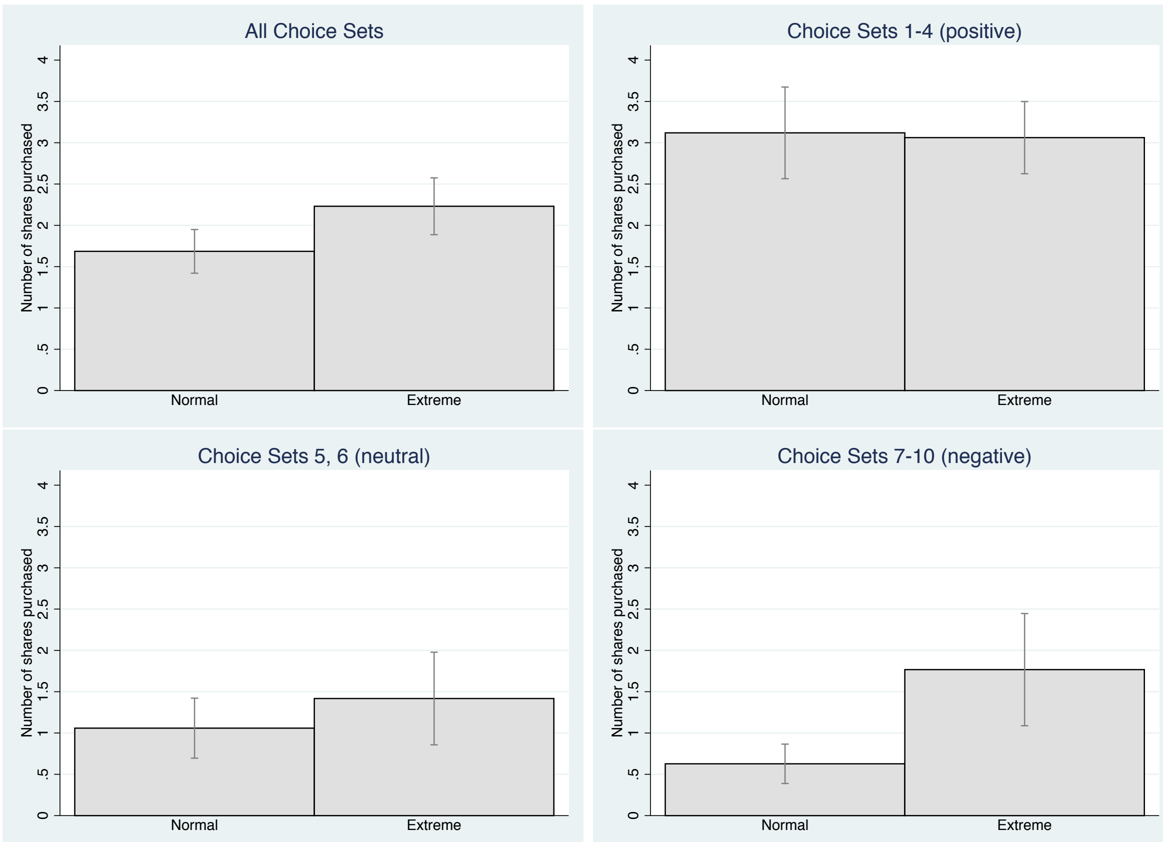
On average, subjects invest about 525 of their 1,000 Taler in stocks. I.e., on average, subjects invest slightly more than half of their initial endowment in each decision task in risky stocks and keep slightly less than half of the endowment in the (non-interest paying) risk-free asset. This number is relatively constant across all 10 choice sets of the experiment. The average number of shares purchased equals 10, and subjects purchase 3 different stocks in each decision situation on average.

Figure 1 displays the average number of shares of the manipulated stock purchased for each category of stock that is manipulated (positive, neutral, and negative), grouped by whether the treated stock exhibits a normal or an extreme return in the period preceding the purchase decision (Period 0). As an example, across all choice sets, the average number of shares purchased of the respective manipulated stock equals about 1.7 when the stock exhibits a normal return in Period 0; with an extreme return in Period 0, the number increases to about 2.2, which is an increase by

[16] In our robustness tests reported in Appendix F, we show that our results are not substantially changed when volume is computed as the product of the number of stock shares purchased and the corresponding stock prices.

Figure 1: Extreme Returns and Number of Shares Purchased

This figure displays the number of manipulated shares purchased in the choice sets of the experiment for each category of stock that is manipulated and the corresponding confidence intervals (95%). *Normal* represents the control condition for a given choice set; *Extreme* represents the treatment condition for a given choice set. The data of all subjects is pooled. The total number of observations equals 1,170 for all stocks (468 for positive and negative stocks, respectively, and 234 for neutral stocks).



almost 30%. As indicated by the higher average purchase volumes in Choice Sets 1 to 4 compared to Choice Sets 7 to 10, subjects purchase more positive than negative manipulated stocks. With respect to positive stocks, extreme returns of +10 instead of normal returns of +1 have virtually no impact on the number of shares purchased. For negative stocks however, the purchase volume increases from 0.6 to 1.8 when the last-period return of a given stock equals the extreme −10 instead of the normal −1.

In line with our hypothesis H1, Wilcoxon rank-sum tests show that the increase in purchase volume across all choice sets as well as for negative stocks is significant at the 1% level. The changes in purchase volume between the normal and the extreme condition are insignificant as far as positive and neutral stocks are concerned.

Table 3 displays the results of an OLS regression in which the dependent variable is the number

Table 3: Extreme Returns and Number of Shares Purchased

This table contains the coefficients and t-statistics (in parentheses) of OLS regressions in which the dependent variable is the number of shares of the manipulated stock (treatment or control) purchased. *Extreme prior return* represents a dummy variable which is equal to one if the return of the treated stock in the period preceding the purchase decision (Period 0) is extremely high or low (i.e., equal to 10 in absolute size); *Risk tolerance* is subjects' self-assessed risk tolerance in the general domain, measured on a scale from 0 (lowest) to 10 (highest); *Age* is subjects' age, measured in years; *Male* is a dummy variable which is equal to one if a subject is male; *Earnings in preceding decision* denotes the amount of Taler a subject earned in the preceding decision situation; *Number of decision* denotes the number of the respective decision for a subject (ranging from 1 to 10); *Session* is a dummy variable representing the different sessions of the experiment; *Rank of extreme prior return* is a dummy variable indicating whether the extreme prior return of the treated stock is a unique maximum or minimum; *Degree* is the degree with which a subject expects to graduate; *Field of study* represents subjects' main field of study; *Statistics knowledge* is subjects' self-assessed knowledge in statistics. Standard errors are clustered at the subject level. *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) All Choice Sets	(2) CS 1-4 (positive)	(3) CS 5&6 (neutral)	(4) CS 7-10 (negative)
Extreme prior return	0.455**	-0.173	0.443	0.956***
	(1.98)	(-0.53)	(1.11)	(2.73)
Risk tolerance	0.235***	0.208**	0.146**	0.306
	(2.63)	(2.38)	(2.41)	(1.45)
Age	-0.056***	-0.132***	-0.060**	0.024
	(-2.73)	(-2.90)	(-2.09)	(0.63)
Male	0.652*	1.461***	0.392	-0.057
	(1.85)	(2.87)	(1.27)	(-0.07)
Earnings in preceding decision	0.000	0.001	0.001	-0.000
	(0.48)	(1.58)	(1.10)	(-0.13)
Number of decision	0.029	-0.001	-0.079	0.076
	(0.64)	(-0.02)	(-1.45)	(0.93)
Constant	1.690*	4.965***	2.512**	-1.467
	(1.83)	(3.45)	(2.31)	(-0.84)
Session	Yes	Yes	Yes	Yes
Rank of extreme prior return	Yes	Yes	Yes	Yes
Degree	Yes	Yes	Yes	Yes
Field of study	Yes	Yes	Yes	Yes
Statistics knowledge	Yes	Yes	Yes	Yes
N	1,170	468	234	468
R^2	0.07	0.14	0.14	0.10

of shares of the manipulated stock (treatment or control) purchased in a given decision situation. The main explanatory variable is a dummy variable which is equal to one if the return of the treated stock in the period preceding the purchase decision is extremely high or low (i.e., equal to $+10$ instead of $+1$ for positive stocks and -10 instead of -1 for negative stocks). Since we include 10 observations for each subject, standard errors are clustered at the subject level.

The coefficient of the treatment dummy is significantly positive, indicating that about 0.5 additional shares are purchased when the respective stock exhibits extreme returns in the preceding period, which is in line with our hypothesis H1. Importantly, we find that this effect is mainly driven by investors' buying of extreme negative stocks. The treatment dummy is insignificant as far as positive and neutral stocks are concerned; regarding negative stocks however, the coefficient is significantly positive. Observing an extreme low return in the period preceding the purchase decision increases the number of negative stock shares purchased by about 1. Compared to the baseline number of shares of negative stocks purchased of about 0.6, this is an increase by more than 150%. Note that we control for whether the extreme prior return of the treated stock represents a unique maximum or minimum among all prior returns (e.g., if there is no further stock with a return of +10 in Period 0 in the case of positive manipulated stocks; this is the case in some choice sets of our experiment); in so doing, we ensure that the rank effect (Hartzmark, 2015) does not confound our results.

Higher self-assessed risk tolerance increases the number of shares of the manipulated stock purchased as far as positive and neutral stocks are concerned. Moreover, older subjects buy significantly fewer manipulated stocks (except for negative stocks) and male subjects purchase significantly more shares of positive manipulated stocks. Although the decisions of each subject are independent, we also control for subjects' earnings in the decision task preceding the respective task; as expected, we find no significant effect.[17]

Additional analyses provided in Section 5 reveal that subjects that are likely to base their decisions on Bayesian updating show no attention-driven purchase patterns, which seems plausible. In other words, subjects not following Bayesian updating are most likely to exhibit attention-driven purchase behavior. In addition, the effect of attention on purchase behavior is observed for individuals with lower stock investments and who take less time to make their investment decisions primarily. These findings strengthen the interpretation of our results as evidence of investor attention: individuals with lower stock investments might have lower stock market experience (either in reality and/or in our experiment) and are thus looking for cues where to invest their money; for these individuals, attention-grabbing stock characteristics might represent such cues. Subjects with lower decision time might strive to make quick and intuitive decisions; for these individuals, extreme prior returns are a quick and easy way to determine where to invest.

[17]Using the switching point from the Holt and Laury (2002) lottery task instead of self-assessed risk tolerance leaves our main results qualitatively unchanged. To rule out the possibility that our results are influenced by the definition of purchase volume, we repeat our main analysis in Table 13 in Appendix F but substitute the volume of shares purchased, defined as the product of quantity and price, for the mere number of shares purchased as the dependent variable. We find that our main results are qualitatively unchanged. To rule out that our results depend on the specific regression model used, Table 14 in Appendix F repeats our main analysis but uses a Tobit specification instead of the OLS model. As before, we observe that our main results are almost unchanged. In addition, we find that subjects do not react differently to the treatment in earlier or later decisions; while subjects' learning could improve later decisions, their exhaustion might have the opposite effect. Our results suggest that neither effect is relevant or that both effects cancel each other out.

Table 4: Extreme Returns and Investment in Stocks

This table contains the coefficients and t-statistics (in parentheses) of OLS regressions; the dependent variable in Column 1 is the total amount of Taler invested in stocks in a decision situation; the dependent variable in Column 2 is the total number of stocks purchased in a decision situation; the dependent variable in Column 3 is the number of different stocks purchased in a decision situation. *Extreme prior return* represents a dummy variable which is equal to one if the return of the treated stock in the period preceding the purchase decision (Period 0) is extremely high or low (i.e., equal to 10 in absolute size); *Risk tolerance* is subjects' self-assessed risk tolerance in the general domain, measured on a scale from 0 (lowest) to 10 (highest); *Age* is subjects' age, measured in years; *Male* is a dummy variable which is equal to one if a subject is male; *Earnings in preceding decision* denotes the amount of Taler a subject earned in the preceding decision situation; *Number of decision* denotes the number of the respective decision for a subject (ranging from 1 to 10); *Session* is a dummy variable representing the different sessions of the experiment; *Rank of extreme prior return* is a dummy variable indicating whether the extreme prior return of the treated stock is a unique maximum or minimum; *Field of study* represents subjects' main field of study; *Degree* is the degree with which a subject expects to graduate; *Statistics knowledge* is subjects' self-assessed knowledge in statistics. Standard errors are clustered at the subject level. *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) Amount in Stocks	(2) Number of stocks	(3) Number of stock types
Extreme prior return	1.475	-0.087	0.062
	(0.09)	(-0.29)	(0.77)
Risk tolerance	33.277***	0.723***	0.026
	(2.70)	(2.84)	(0.47)
Age	-14.625***	-0.202**	-0.024
	(-3.31)	(-2.40)	(-1.31)
Male	140.412**	2.494**	-0.392
	(2.55)	(2.17)	(-1.64)
Earnings in preceding decision	-0.022	-0.001*	-0.000
	(-1.37)	(-1.95)	(-0.37)
Number of decision	-5.571**	-0.131**	-0.056***
	(-2.17)	(-2.32)	(-3.25)
Constant	696.534***	10.846***	3.554***
	(3.45)	(2.68)	(3.90)
Session	Yes	Yes	Yes
Rank of extreme prior return	Yes	Yes	Yes
Degree	Yes	Yes	Yes
Field of study	Yes	Yes	Yes
Statistics knowledge	Yes	Yes	Yes
N	1,170	1,170	1,170
R^2	0.23	0.22	0.16

4.1.2 Attention Effects in Portfolio Composition

The analyses presented above focus on the purchasing patterns with respect to the manipulated stocks in the respective choice sets (i.e., they focus on one of the six stocks in each choice set). In this section, we investigate whether attention-driven purchase behavior affects subjects' overall portfolio composition.

As stated above, the average investment amount across all subjects and all choice sets equals about 525 Taler. Column 1 of Table 4 displays the results of an OLS regression in which the dependent variable is the total amount of Taler invested in stocks in a given decision situation. The coefficient on the variable indicating an extreme prior return is insignificant, indicating that our treatment did not make subjects invest more or less in stocks. We further observe that more risk-tolerant subjects (as measured with the self-assessment), younger subjects, and men invest more in stocks. Column 2 shows that the total number of stocks purchased in a given decision situation is unaffected, too. Finally, Column 3 suggests that extreme prior returns do not affect the number of different stock types subjects invest in (ranging from 0 to 6) for a given decision situation.[18]

In sum, these observations imply that extreme prior returns do not induce subjects to change the split between risky stocks and the risk-free asset, nor to change the total number of shares they purchase or how much they diversify by investing in different types of stocks. Instead, subjects change the allocation of the amount invested in risky assets across the six stocks, purchasing more attention-grabbing stocks in the treatment and fewer non-attention-grabbing stocks. In other words, the presence of attention-grabbing stocks does not increase stock buying. These findings suggest that the demand for attention-grabbing stocks increases at the expense of the demand for non-attention-grabbing stocks. To the extent that attention-grabbing stocks are less profitable than non-attention-grabbing stocks, such behavior is likely to reduce investors' wealth. We resume this debate in Section 6.

4.2 Visual Fixations

With respect to Hypothesis H2, we use eye tracking devices to measure subjects' visual attention and test whether subjects' visual fixations are associated with their stock buying behavior.

4.2.1 Measurement

Visual attention plays a crucial role in decision-making (for a review see Orquin and Mueller Loose (2013)). Empirical evidence suggests that visual attention determines the perception as well as processing of stimuli (Droll, Hayhoe, Triesch, and Sullivan, 2005; Triesch, Ballard, Hayhoe, and Sullivan, 2003). Based on these insights, Orquin and Mueller Loose (2013) argue that visual attention influences individual decision-making by limiting the decision to the fixated stimuli and enhancing the influence of the fixated information.

We measure visual attention patterns by tracking subjects' eye movements, which is in line with studies reporting strong links between eye movements and visual attention (Deubel and Schneider, 1996; Hoffman and Subramaniam, 1995; Kowler, Anderson, Dosher, and Blaser, 1995). Eye movements were recorded with remote binocular Tobii Pro X2-60 eye trackers using a screen with a resolution of 1920×1200 pixels and size of 20.3×12.8 inches. The tracking distance was 50 cm to 80

[18] In unreported regressions (available from the authors upon request), we use a Tobit specification instead of an OLS regression and find that our results are qualitatively unchanged.

cm. Data was gathered at a sampling rate of 60 Hz (about 16.67 ms) with an accuracy of 0.4 degrees and a precision of 0.34 degrees; a standard five-point calibration was applied and a maximum of two recalibrations were conducted.[19] No chin rest was used. Fixation durations exceeding 60 ms were included in the analyses (Komogortsev, Gobert, Jayarathna, Koh, and Gowda, 2010; Salojärvi, Puolamäki, Simola, Kovanen, Kojo, and Kaski, 2005). To analyze the length of the fixation duration on a specific stimulus, non-overlapping areas of interest (AOIs) were defined. In particular, we use AOIs with respect to different pieces of information provided in the table displayed on the experimental screen in each of the ten decision situations.[20] We defined AOIs for each stock (rows) of 807×116 pixels in size. Subjects with corneal irregularity or other eye disease as well as with diopter strength exceeding +/- 2.8 were excluded from participating.

4.2.2 Attention Effects in Stock Buying Behavior

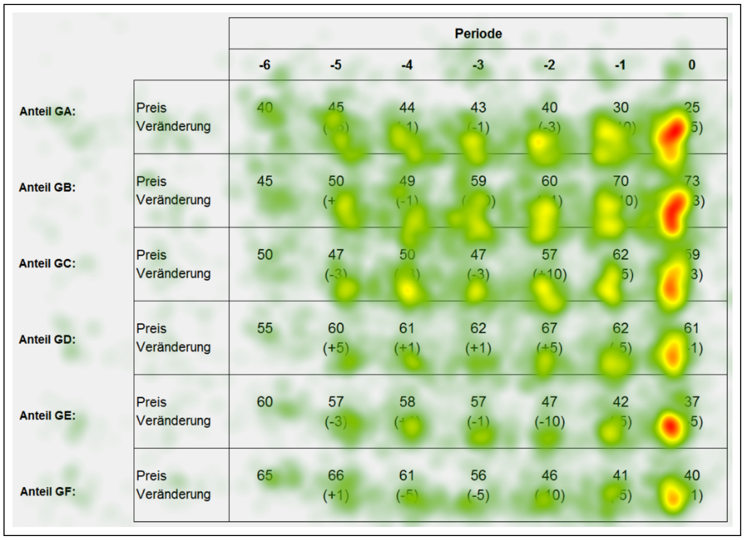
In our analyses, we resort to *fixation duration*, the most widely used measure in eye-tracking research (Holmqvist, Nyström, Andersson, Dewhurst, Jarodzka, and Van de Weijer, 2011). Figure 2 displays the heatmap of absolute fixation durations as an average of all subjects for one of the ten decisions of the experiment. Yellow and red areas indicate locations of relatively longer fixation duration. The main finding is that fixation durations generally increase from left to right, implying that fixation durations are higher for more recent periods and shorter for periods that are further in the past. Independent of the specific decision task, the heatmaps provide a first indication for subjects' strong visual attention to the period prior to the purchase decision (Period 0), i.e., the period manipulated with attention-grabbing stock characteristics in the treatment condition. Assuming that counting consistent with Bayesian updating should result in gaze patterns with equally distributed attention to all periods displayed in the table (i.e., Periods -6 to 0), this observation implies biased visual attention with a strong focus on stock price information of the very period preceding the purchase decision. A further observation is that fixation durations are higher in upper rows than in lower rows; this is consistent with the empirical observation that stocks appearing at the top of a list have higher trading activity and liquidity than stocks appearing at the bottom (Jacobs and Hillert, 2016). Since – as described above – we varied the position of the stock types across choice sets, our results should not be affected.[21]

For the following analyses, we define relative fixation duration as subjects' fixation duration on the manipulated stock AOI relative to the fixation duration on all stock AOIs for each choice set,

[19] The background color of the calibration screen was white.
[20] An example table is provided in Appendix E. The font size was 18pt.
[21] The other nine heatmaps show virtually identical patterns of visual attention.

Figure 2: Heatmap of Absolute Fixation Durations

This figure displays the heatmap of absolute fixation durations of one of the ten decisions in the experiment, averaged over all subjects.



measured in percent. Again, we pool the data from all subjects. The average number of stocks fixated in each decision situation equals 5.5. On average, subjects allocate 19% of their fixation duration on the manipulated stock AOIs across the different choice sets. Subjects' relative fixation duration on the manipulated stock AOI is substantially higher in the treatment (20.9%) than in the control (17.2%) condition. Wilcoxon rank-sum tests reveal that subjects' relative fixation duration on the manipulated stock in the treatment condition is significantly higher (1% level) than in the control treatment as well as compared to equally distributed attention.

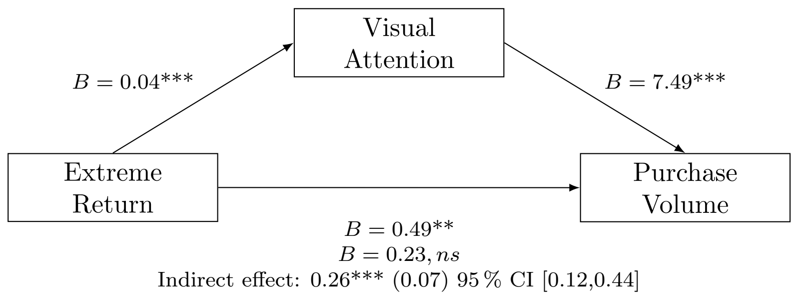
We also predicted that the effects of our treatment on stock purchase volume would be mediated by subjects' visual attention. To investigate this channel of attention, we conduct a mediation analysis, which is displayed in Figure 3.[22] Subjects show a higher purchase volume of manipulated stocks after experiencing extreme returns, $B = 0.49$, $SE = 0.24$, $P = 0.039$, 95% CI (0.02, 0.96)[23], and significantly higher visual attention to those stocks after experiencing extreme returns: $B = 0.04$, $SE = 0.01$, $P = 0.000$, 95% CI (0.02, 0.05). After controlling for visual attention, the treatment is no longer a significant predictor of stock purchase volume: $B = 0.23$, $SE = 0.21$, $P = 0.280$, 95% CI (-0.19, 0.65). Testing the significance of the natural indirect effect using bootstrap estimation results in a significant indirect coefficient: $B = 0.26$, $SE = 0.07$, $P = 0.000$, 95% CI (0.12, 0.44).

[22]We control for risk tolerance, age, gender, subjects' earnings in the preceding decision, the number of the decision, and the ranking of the extreme return.

[23]For our mediation analyses we used a slightly different set of control variables compared to our regression analyses in Section 4.1.1 (without multicategorical independent variables), which explains the small deviations in results.

Figure 3: The Effect of Extreme Returns on Purchase Volume Through Visual Attention

This figure displays unstandardized regression coefficients from mediation analysis obtained through bootstrapping. The range in brackets represents the bias-corrected CI of the natural indirect effect.



That is, extreme returns increase subjects' stock purchase volume through channeling subjects' visual focus on the respective stock. In sum, our mediation analysis shows that the relationship between exposure to extreme returns and stock purchase behavior is indeed explained by visual attention to the manipulated stocks.

Table 5 displays the results of an OLS regression in which the dependent variable is the number of shares of the manipulated stock (treatment or control) purchased in a given decision situation.[24] The main explanatory variable is subjects' relative fixation duration on the manipulated stock AOI. Thus, we replace the treatment dummy from our previous analyses (attention-grabbing characteristic) by the alternative measure of attention reflecting visual fixation. Standard errors are clustered at the subject level. As before, we control for risk tolerance, age, gender, subjects' earnings in the preceding decision, the number of the decision, the experimental session, the rank effect, as well as subjects' educational degree, field of study, and statistical knowledge.

As shown in the mediation analyses and in line with our Hypothesis H2, the coefficient of the relative fixation duration variable is significantly positive. A higher allocation of fixation duration on the manipulated stock is positively correlated with subjects' purchase volume of the respective stock. In detail, the results indicate that an increase in the relative fixation duration by 10 percentage points increases the number of purchased shares of the manipulated stock by about 0.75. This is an increase by almost 40% compared to the average number of 1.9 purchased shares of the manipulated stock across all choice sets. Furthermore, we find that the attention effect is largest for negative stocks, which is in line with the observed asymmetry in Table 3: the effect is almost three times as large as for positive stocks and more than five times as large as for neutral stocks. In other words,

[24]The total number of observations in Table 5 equals 114 (subjects) $\cdot$ 1 (manipulated stock) $\cdot$ 10 (decisions) $= 1,140$.

Table 5: Relative Fixation Duration and Number of Shares Purchased

This table contains the coefficients and t-statistics (in parentheses) of OLS regressions in which the dependent variable is the number of shares of the manipulated stock (treatment or control) purchased. *Relative fixation duration* represents subjects' relative fixation duration on the manipulated stock AOI relative to the fixation duration on all stock AOIs for each choice set in percent; *Risk tolerance* is subjects' self-assessed risk tolerance in the general domain, measured on a scale from 0 (lowest) to 10 (highest); *Age* is subjects' age, measured in years; *Male* is a dummy variable which is equal to one if a subject is male; *Earnings in preceding decision* denotes the amount of Taler a subject earned in the preceding decision situation; *Number of decision* denotes the number of the respective decision for a subject (ranging from 1 to 10); *Session* is a dummy variable representing the different sessions of the experiment; *Rank of extreme prior return* is a dummy variable indicating whether the extreme prior return of the treated stock is a unique maximum or minimum; *Degree* is the degree with which a subject expects to graduate; *Field of study* represents subjects' main field of study; *Statistics knowledge* is subjects' self-assessed knowledge in statistics. Standard errors are clustered at the subject level. *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) All Choice Sets	(2) CS 1-4 (positive)	(3) CS 5&6 (neutral)	(4) CS 7-10 (negative)
Relative fixation duration	7.488***	4.877***	2.239**	12.595**
	(4.58)	(3.81)	(2.37)	(2.35)
Risk tolerance	0.236***	0.216**	0.134**	0.277
	(2.88)	(2.42)	(2.30)	(1.62)
Age	-0.071***	-0.129***	-0.067**	0.005
	(-3.40)	(-3.03)	(-2.57)	(0.19)
Male	0.612*	1.543***	0.270	-0.068
	(1.80)	(3.15)	(0.86)	(-0.10)
Earnings in preceding decision	0.000	0.000	-0.001	-0.000
	(0.14)	(0.71)	(-1.27)	(-0.58)
Number of decision	0.062	0.035	-0.074	0.079
	(1.28)	(0.60)	(-1.35)	(1.01)
Constant	0.632	3.389**	4.018***	-2.703
	(0.56)	(2.24)	(3.03)	(-1.17)
Session	Yes	Yes	Yes	Yes
Rank of extreme prior return	Yes	Yes	Yes	Yes
Degree	Yes	Yes	Yes	Yes
Field of study	Yes	Yes	Yes	Yes
Statistics knowledge	Yes	Yes	Yes	Yes
N	1,140	456	228	456
R^2	0.15	0.19	0.15	0.21

the asymmetric effect of investor attention is reflected in these patterns of visual attention.

In a robustness test reported in Appendix F (Table 15), we further show that our asymmetric treatment effect is not driven by different general attention levels to positive and negative stocks because they have been shown in different rows of the information table provided to subjects. The analyses are restricted to choice sets with positive and negative manipulated stocks in the same row (second row) of the information table provided to the subjects. The results show that althought positive and negative manipulated stocks are shown in the same row, extreme returns significantly increase visual attention to negative stocks, but not to positive stocks.

5 Discussion of Investor Attention and Alternative Explanations

This section discusses the interpretation of our results as evidence of investor attention (Section 5.1) as well as potential alternative drivers of our results (Section 5.2); the latter are unrelated to investor attention but might lead to observationally similar trading patterns.

5.1 Interpretation as Investor Attention

Since the concept of Bayesian updating is key to separate rational from non-rational subjects in our experimental design, we first examine whether subjects not following the notion of Bayesian updating are indeed influenced by attention to a greater extent than subjects adhering to Bayesian updating. Of the 117 subjects, 31 subjects (i.e., about one fourth) never purchase shares of negative stocks. These subjects are most likely to use the optimal Bayesian approach and identify positive and neutral stocks by counting the number of price increases from Period -6 to Period 0. Columns 1 and 2 of Table 6 split the sample between these two groups of subjects and repeat our regression. As expected, the coefficient on the dummy variable indicating extreme prior returns is insignificant for Bayesian subjects and significantly positive for all other subjects.[25] This result is consistent with attention-driven purchase behavior that violates Bayesian updating.

In Columns 3 and 4 of Table 6, we implement a split by the median amount of Taler invested in stocks in a decision situation (487 Taler). The significantly positive coefficient on extreme prior returns is observed for decision situations with below-median investment amounts only.[26] This might indicate that subjects that are generally less willing to invest in stocks (and potentially less experienced with stock investments) are more likely to exhibit attention-driven purchase behavior while more experienced subjects do not make purchases based on attention-grabbing stock characteristics.

In Columns 5 and 6 of Table 6 reveal that attention-driven purchase behavior is observed for subjects that take less time to make their decisions: the significantly positive coefficient is only observed in situations in which subjects need to not take more time than the median time of 31 seconds to make their investment decisions.[27] It is possible that extreme prior returns facilitate fast decisions in that subjects quickly decide to purchase the attention-grabbing stocks. Alternatively, for subjects that want to make a quick decision, it might be easiest to simply pick stocks that catch

[25]In principle, the coefficient might be significantly positive for Bayesian subjects if these subjects purchase positive and neutral stocks based on extreme returns in the preceding period.

[26]The same qualitative results are obtained when the median amount is computed on the subject level instead of the choice set level.

[27]The same qualitative results are obtained when the median time is computed on the subject level instead of the choice set level.

Table 6: Extreme Returns and Number of Shares Purchased: Investor Heterogeneity

This table contains the coefficients and t-statistics (in parentheses) of OLS regressions in which the dependent variable is the number of shares of the manipulated stock (treatment or control) purchased. *Extreme prior return* represents a dummy variable which is equal to one if the return of the treated stock in the period preceding the purchase decision (Period 0) is extremely high or low (i.e., equal to 10 in absolute size); *Risk tolerance* is subjects' self-assessed risk tolerance in the general domain, measured on a scale from 0 (lowest) to 10 (highest); *Age* is subjects' age, measured in years; *Male* is a dummy variable which is equal to one if a subject is male; *Earnings in preceding decision* denotes the amount of Taler a subject earned in the preceding decision situation; *Number of decision* denotes the number of the respective decision for a subject (ranging from 1 to 10); *Session* is a dummy variable representing the different sessions of the experiment; *Rank of extreme prior return* is a dummy variable indicating whether the extreme prior return of the treated stock is a unique maximum or minimum; *Field of study* represents subjects' main field of study; *Degree* is the degree with which a subject expects to graduate; *Statistics knowledge* is subjects' self-assessed knowledge in statistics. Standard errors are clustered at the subject level. *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	Bayesian		Amount in Stocks		Time Needed	
	(1) Yes	(2) No	(3) $\leq$ p50	(4) $>$ p50	(5) $\leq$ p50	(6) $>$ p50
Extreme prior return	-0.114	0.697**	0.296**	0.686	0.805**	0.179
	(-0.32)	(2.39)	(2.25)	(1.49)	(2.21)	(0.57)
Risk tolerance	0.230***	0.247*	0.012	0.373**	0.292**	0.176**
	(4.61)	(1.90)	(0.46)	(2.60)	(2.00)	(2.25)
Age	-0.071*	-0.053*	-0.023**	-0.011	-0.046	-0.076***
	(-1.88)	(-1.91)	(-2.23)	(-0.26)	(-1.28)	(-3.07)
Male	0.937**	0.442	0.203	0.220	0.658	0.577*
	(2.70)	(0.89)	(1.20)	(0.40)	(1.35)	(1.78)
Earnings in preceding decision	0.000	0.000	-0.000	0.000	0.000	0.000
	(0.09)	(0.32)	(-0.22)	(0.43)	(0.26)	(0.17)
Number of decision	-0.014	0.043	-0.001	0.086	0.039	0.088
	(-0.19)	(0.77)	(-0.03)	(0.95)	(0.61)	(1.59)
Constant	1.359	2.244*	1.456***	0.868	0.222	3.158***
	(1.30)	(1.83)	(2.80)	(0.53)	(0.15)	(3.13)
Session	Yes	Yes	Yes	Yes	Yes	Yes
Rank of extreme prior return	Yes	Yes	Yes	Yes	Yes	Yes
Degree	Yes	Yes	Yes	Yes	Yes	Yes
Field of study	Yes	Yes	Yes	Yes	Yes	Yes
Statistics knowledge	Yes	Yes	Yes	Yes	Yes	Yes
N	310	860	586	584	594	576
R^2	0.13	0.08	0.08	0.07	0.09	0.07

their attention. Both mechanisms support the interpretation as attention-driven purchase behavior.

5.2 Alternative Explanations

Diversification Motives Since the six stocks are uncorrelated with each other, adding stocks to subjects' portfolios might add value in terms of diversification (Markowitz, 1952). There are three reasons why diversification motives cannot explain our findings.

First, adding stocks with negative expected returns which systematically lose in value cannot be made for reasons related to diversification. In other words, investors should never invest in negative stocks in our experiment (i.e., $-$ stocks and $--$ stocks). If subjects wanted to diversify their portfolios, they should purchase positive and neutral stocks only. In fact, Weber and Camerer

(1998) and Weber and Camerer (1992) demonstrate that Bayesian utility optimizing investors should never hold $-$ and $--$ stocks in the context of the experimental setting on which our analysis is based.

Second, the asymmetric purchase patterns documented above might arise if subjects exhibit a two-step search process in each choice set: they might start by buying positive stocks (not driven by extreme returns) and then search for additional stocks in order to diversify. In this second search step, subjects might see no use in purchasing additional positive stocks but shares of stocks with a lower correlation with those already selected (such as neutral and negative stocks). It is possible that stocks with extreme returns are most salient and therefore more likely to be chosen in this second search step. However, as described above, investors should never invest in negative stocks in our experiment. In addition, it is unlikely that purchase behavior in the first step of this hypothetical search process is not driven by extreme returns while extreme returns drive purchases in the second step. These conclusions are further supported by the observation that extreme returns do not significantly increase the purchase volume of neutral stocks (see Table 3).

Third, assuming subjects have the tendency to buy negative stocks in order to diversify their portfolio, price decreases by -10 Taler and by -1 Taler for a given negative stock should have the same effect on subjects' purchase behavior. Yet, we do only observe an increased purchase volume for negative stocks with extreme returns in the last period. This pattern cannot be explained by diversification motives.

Investor Beliefs A further challenge to our results is the possibility that our finding is rather driven by investors' beliefs instead of their attention. The tendency to purchase shares of stocks which have previously lost in value could be driven by the expectation of mean-reverting stock prices. Following this reasoning, shares of stocks with negative returns in the previous period (i.e., -1 Taler or -10 Taler) should be more likely to be purchased than shares of stocks with positive returns. In addition, shares of stocks with extreme negative returns in the previous period (i.e., -10 Taler) might be more likely to be purchased than shares of stocks with less extreme negative returns. This could lead to the observed patterns of purchases of shares with previous negative extreme returns. Although the belief in mean reversion is incorrect in our design, we cannot fully rule out that subjects formed such beliefs. However, if this explanation were valid, we should observe that shares of positive stocks should be bought less compared to negative stocks, most notably if the increase in the preceding period is as high as 10 Taler. We do not observe such patterns; positive stocks exhibit substantially higher purchase volumes than negative stocks on average.

Further, it could be the case that a particular subset of our subjects believe in mean reversion and drive our results. We therefore conduct additional regressions to those in Section 4.1.1 and our mediation analyses in Section 4.2.2 with a control variable capturing whether subjects follow a buying strategy in line with a belief in mean reversion. We use a dummy variable which is equal to one if a given subject invests in a stock (other than the manipulated stock) with a prior negative return in the respective decision situation. Table 7 shows that the coefficient of the treatment variable is significantly positive in the cross-section, insignificant as far as positive and neutral stocks are concerned, and significantly positive for negative stocks. The size of the coefficients and the significance levels are similar when including the control variable for a potential belief in mean reversion. Our dummy variable for a belief in mean reversion shows no significant correlation with the number of negative stock shares purchased. In Appendix F (Figure 5) we report the results for mediation analyses with control for beliefs in mean reversion. The results are qualitatively unchanged. In addition, we run these regression analyses with an alternative control variable capturing whether subjects follow a buying strategy in line with a belief in mean reversion across all ten decisions. The results for our treatment effect remain qualitatively unchanged (Appendix F, Table 16).

Alternatively, subjects might believe in momentum. In this case, shares of stocks with extreme negative (positive) returns in the previous period might be deemed more likely to exhibit negative (positive) returns in the next period. As with mean reversion, this belief is incorrect in our experimemtal design. Yet, if subjects still believed in momentum, we should observe a significantly negative effect of negative (extreme) returns and a significantly positive effect of positive (extreme) returns on stock purchases. However, neither of these patterns is observed in our data.

Budget Constraints A potential strategy of subjects is allocating a fixed budget (in Taler) to each stock. Following this reasoning, price decreases by -10 Taler instead of -1 Taler allow for a higher number of share purchases for a given negative stock, which might lead to a comparable behavior of purchasing shares of stocks which have experienced extreme negative returns previously.

However, by the same argument, price increases by $+10$ Taler instead of $+1$ Taler for positive stocks should decrease the number of shares purchased for a given stock. Yet we do not observe such behavior and therefore conclude that it is unlikely to drive our results.

6 Implications for Investor Wealth

Barber and Odean (2008) find that retail investors are net buyers of stocks that catch their attention. They concede that investors' utility might increase in cases in which attention-grabbing features of a

Table 7: Extreme Returns and Number of Shares Purchased with Control for Beliefs in Mean Reversion

This table contains the coefficients and t-statistics (in parentheses) of OLS regressions in which the dependent variable is the number of shares of the manipulated stock (treatment or control) purchased. *Extreme prior return* represents a dummy variable which is equal to one if the return of the treated stock in the period preceding the purchase decision (Period 0) is extremely high or low (i.e., equal to 10 in absolute size); *Risk tolerance* is subjects' self-assessed risk tolerance in the general domain, measured on a scale from 0 (lowest) to 10 (highest); *Age* is subjects' age, measured in years; *Male* is a dummy variable which is equal to one if a subject is male; *Earnings in preceding decision* denotes the amount of Taler a subject earned in the preceding decision situation; *Number of decision* denotes the number of the respective decision for a subject (ranging from 1 to 10); *Invest in other neg. return stock* is the control variable for beliefs in mean reversion, a dummy variable which is equal to one if the subject invested in a stock (other than the manipulated stock) with a prior negative return in the respective decision situation; *Session* is a dummy variable representing the different sessions of the experiment; *Rank of extreme prior return* is a dummy variable indicating whether the extreme prior return of the treated stock is a unique maximum or minimum; *Degree* is the degree with which a subject expects to graduate; *Field of study* represents subjects' main field of study; *Statistics knowledge* is subjects' self-assessed knowledge in statistics. Standard errors are clustered at the subject level. *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) All Choice Sets	(2) CS 1-4 (positive)	(3) CS 5&6 (neutral)	(4) CS 7-10 (negative)
Extreme prior return	0.464**	-0.108	0.463	0.957***
	(2.00)	(-0.33)	(1.13)	(2.79)
Risk tolerance	0.241**	0.248**	0.127**	0.307
	(2.55)	(2.60)	(2.24)	(1.43)
Age	-0.057***	-0.133***	-0.062**	0.024
	(-2.73)	(-2.94)	(-2.43)	(0.60)
Male	0.641*	1.421***	0.351	-0.065
	(1.77)	(2.82)	(1.20)	(-0.08)
Earnings in preceding decision	0.000	0.000	-0.001	-0.000
	(0.20)	(0.52)	(-1.01)	(-0.19)
Number of decision	0.028	0.006	-0.068	0.077
	(0.62)	(0.11)	(-1.17)	(0.94)
Invest in other neg. return stock	-0.334	-1.264***	0.655	-0.095
	(-1.13)	(-3.51)	(1.49)	(-0.16)
Constant	2.014**	5.710***	3.182**	-1.395
	(2.11)	(3.92)	(2.27)	(-0.82)
Session	Yes	Yes	Yes	Yes
Rank of extreme prior return	Yes	Yes	Yes	Yes
Degree	Yes	Yes	Yes	Yes
Field of study	Yes	Yes	Yes	Yes
Statistics knowledge	Yes	Yes	Yes	Yes
N	1,170	468	234	468
R^2	0.07	0.16	0.16	0.10

stock match features which increase investors' utility. Importantly, they argue that if the opposite is true, i.e., attention-grabbing features coincide with negative utility, investors' utility might actually decrease. Some empirical evidence suggests that investors indeed buy attention-grabbing stocks with features that coincide with negative wealth implications. Da, Engelberg, and Gao (2011) find that stocks with search frequency spikes exhibit higher prices in the next two weeks and price reversals within the year. Given the empirical evidence for retail buying pressure for attention-grabbing stocks (Barber and Odean, 2008), this could indicate that attention-induced stock purchases are followed by a price reversal (i.e., negative returns); leading to potential wealth losses. Further, Kumar, Ruenzi, and Ungeheuer (2020) find a significant underperformance of attention-catching stocks – daily winners and losers – after they are bought by retail investors. On the other hand, Gargano and Rossi (2018) show that attentive investors achieve higher risk-adjusted returns and portfolio Sharpe ratios.

However, whether attention-attracting features of a stock and investor wealth are positively or negatively correlated is hardly discernible in real-world trading data. Our experimental design allows for a clear deduction of implications with respect to investors' financial position at the individual level: First, stock quality can be observed based on past stock prices. Subjects can infer stock quality from the sign of returns only but not from the absolute amount of price changes. Thus, in theory, we should observe no treatment effect: extreme returns are irrelevant for decision-making as they are not correlated with fundamentals of a stock (which is clear from the instructions). Second, attention-driven purchase behavior regarding stocks with negative extreme prior returns (as observed by Barber and Odean (2008)) reduces investors' financial positions in situations in which such prior returns are associated with stocks with negative expected returns.

Thus, based on our findings, we contend that subjects' tendency to focus on stocks with extreme returns makes them systematically lose money in our experiment. While negative extreme prior returns are not necessarily associated with stocks with negative expected returns outside our laboratory setting, our results indicate that attention-driven purchase behavior even occurs in situations in which stocks with negative expected returns are easy to identify and in which attention-driven purchase behavior reduces investors' wealth. While we do not claim that attention-driven purchase behavior always reduces investors' wealth in real-world financial markets, our results imply that return patterns catching investors' attention have the potential to dominate decision criteria related to expected returns and Bayesian updating.

7 Discussion and Conclusion

This paper establishes a causal link between investor attention and stock purchase behavior at the individual level. Based on an incentivized laboratory experiment, we find that extreme returns affect purchase patterns of stocks. In contrast to empirical analyses of stock market data, investor preferences or beliefs cannot explain these trading patterns. In particular, we uncover an asymmetric attention effect as shares of stocks with recent extreme negative returns are more likely to be purchased than shares of stocks with recent less extreme negative returns. Comparable patterns are not observed for stocks with extreme positive returns. At the portfolio level, we observe that the demand for attention-grabbing stocks increases at the expense of the demand for non-attention-grabbing stocks. Moreover, we provide evidence for subjects' visual attention to the respective stock's information mediating our treatment effect. Extreme returns increase subjects' stock purchase volume through channeling subjects' visual focus on the respective stock. Importantly, purchase patterns driven by attention-grabbing characteristics even occur if they reduce subjects' returns.

Our finding of an asymmetric effect on investors' purchase behavior is in line with previous research showing that individuals behave differently in the face of positive and negative information or events in stock markets. Empirical research finds evidence of the *negativity effect* hypothesis showing that announcement effects of consumer sentiment news on stock markets can only be observed for the release of bad sentiment news (Akhtar, Faff, Oliver, and Subrahmanyam, 2013). Remarkably, this effect seems to be more pronounced for salient stocks. With respect to investor attention, an indication of asymmetric effects is also present in previous empirical findings. In particular, Barber and Odean (2008) investigate three types of retail investors representing individual investors (customers at a large discount brokerage, a large retail brokerage, and a small discount brokerage) as opposed to professional money managers. While professional managers do not exhibit purchase patterns driven by attention, they report the tendency of investors to be net buyers of previous extreme losers and *not* to be net buyers of previous extreme winners for two of the three retail investor groups. Similar tendencies can be found with respect to investors' stock evaluations, as studies suggest that extreme returns play a significant role in the cross-sectional pricing of stocks (*MAX effect*) (Bali, Cakici, and Whitelaw, 2011; Zhong and Gray, 2016).

But why do subjects buy shares of extreme negative stocks which harms their financial performance in the experiment and in turn considerably minimizes their payment? This result is in line with the tendency of retail investors to be net buyers of previous extreme losers found by Barber and Odean (2008). We can exclude rational beliefs in mean reversion as a potential alternative explanation for purchases of shares with extreme negative returns. Thus, in our setup, attention-driven purchase behavior in fact constitutes a bias. We relate the asymmetry in subjects' actual purchase patterns to the general insight that negative outcomes are experienced more strongly than positive outcomes when making decisions under risk (such as in prospect theory described in Kahneman and Tversky (1979)). Our results suggest that the asymmetric mechanisms underlying investors' attention in the stock market are associated with subjects' visual attention patterns. Thus, we argue that our findings are likely to arise from an attention-driven bias, where extreme negative returns seem to influence individuals' decision-making more strongly than extreme positive returns. In fact, psychological research supports this notion; several studies indicate that losses lead to more attention than equivalent gains. People tend to narrow and focus their attention on events or information that elicit a negative state to a greater degree than to positive or neutral objects (see Peeters and Czapinski (1990) for a review). Yechiam and Hochman (2013) actually describe losses as "modulators of attention" and show that even in the absence of loss aversion, losses have distinct effects on attention and subsequent behavior.[28]

Our results offer various avenues for future research. As an example, while this experiment focuses on purchase decisions, future experimental studies might additionally include selling decisions to test whether attention is in fact of minor importance on the sell side, as suggested by previous work Barber and Odean (2008). Moreover, it might be interesting to investigate whether the asymmetric effects of attention exist in markets other than the stock market. Moreover, the channels via which the asymmetry in investors' purchase behavior arises might be further investigated.

[28]Yechiam and Hochman (2013) show that, as predicted by their attentional model, asymmetric effects of losses on behavior emerge where gains and losses are presented separately but not concurrently. This seems to contradict our findings, as we confront participants with positive, neutral, and negative stocks concurrently. However, in each decision task, we only vary one return (normal and extreme condition).

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Appendices

A Experiment Instructions

(translated from German)

A.1 Introduction

You will be taking part in an economics related experiment. The experiment will last approximately 1 hour. For the duration of the experiment, we ask that you observe a few rules: starting now we ask that you refrain from any sort of communication. If at any point you have a question, please notify us by raising your hand to be visible outside of the cubicle. We will then come to you to answer any questions. If you do not adhere to this rule, this will lead to an automatic exclusion from the experiment and from payment.

We also ask you to turn off your cell phones and other devices, or at least to put them on silent, and to pack them away with your bag or belongings. We do not want you or other subjects to be disturbed or distracted.

A.2 General Explanation of Eye-Tracking

We would like to provide you with some general information on the eye-tracking technology that is used in this experiment. The eye tracking technology is used to capture movements of your eyes. Eye-tracking adds a new dimension to data gathering by allowing us to measure where you are looking on your monitor. The eye-tracking data, as well as all other data collected during the experiment, are recorded anonymously. Only data needed to calculate the direction of your eye movements are recorded. Neither your face nor any other features that could provide information about you are recorded.

The measurements are made by the black bar found at the bottom edge of your monitor. With this, your eyes are illuminated with an infrared light. This is the faint red light you will occasionally see flashing in the black bar. The illumination of your eyes to measure your viewing direction is harmless to your health. You can review this again in the consent form that we have given you

Please read and sign the consent form for the eye-tracking experiment. If you have any questions, please notify us from your cabin and we will come to you. Once you have signed your consent form, please hand this to us as we walk by your cubicle to collect the forms.

A.3 Introduction to the Experiment

You are taking part in an experiment on investment decisions. Decision-making situations will be simulated in which you can decide on how to invest in company shares. Depending on your investment decisions, you will be rewarded at the end of the experiment.

To start the experiment, detailed introductions will be displayed on your screen – these extend over several pages. Please read the instructions carefully. They will not be available to you during the experiment. You have enough time to read through the instructions and therefore do not need to hurry. If you have any questions, please ask. Please note that all the instructions for the experiment will be displayed before the experiment starts.

Once you have read the instructions, we will ask you two questions about the rules of the experiment. We want to make sure you understand the design. If you have questions or problems at this point specifically (or to the general experiment), please do not hesitate to contact us. The experiment is anonymous, for that reason you will receive a questionnaire at the end of the experiment that will ask for some sociodemographic information, but not your name. This is then followed by the experiment payout. For the payout, we will call you individually by your cubical number. Only one of the experiment supervisors and you will see what you earned.

A.4 Alignment and Calibration of the Eye-Tracker

Now we will start with the alignment and calibration of your eye-tracker. For the alignment, you will see a window on your monitor in a few moments. This window shows your eyes as white dots. The goal of this step is to position your eyes in the middle of the window. To do so, the bar at the right edge of the window, which indicates your distance, should be at 0.5. If you are at a suitable distance from the monitor, this bar will turn green. To properly align yourself, you can move your chair and monitor. Please make sure that you can still comfortably reach your keyboard and mouse. Once alignment is complete, please wait until all other subjects are also aligned. If you require assistance, please notify a supervisor from your cubicle.

Now we will start the calibration. For this, we ask you to look in the middle of the yellow dot. The yellow dot appears on your monitor and then jumps to four more points on the monitor. We will show you all the calibration points for the test run on your screen now.

A.5 Investment Task

The experiment consists of 2 independent parts.

The purpose of this experiment is to study individual economic decisions. Decision-making situations will be simulated in which you have the opportunity to invest in company shares. The currency in this experiment is *Taler* with an exchange rate of

$$100 \text{ Taler} = €\,1$$

The experiment lasts approximately 60 minutes. If you leave the experiment prematurely, you cannot receive a payment.

After the experiment, you will receive a payout for your participation. The actual amount will depend on your decisions in the experiment. The average payout is around €10. Your actual remuneration may be above or below this.

There is no time limit in any part of this experiment.

A.6 Part 1. Investment Decisions

This part of the experiment is relevant for your payout.

In this part of the experiment, you will be given a total of 10 independent situations, in which you can invest in different company shares. This means that in each respective situation you can buy different shares, which will then be resold in the following period. At the end of each decision situation, you will receive a notification of your monetary balance. The final balance after each situation will be relevant for your payout.

The process is the same in every situation:

1) Buy

In every situation, you have a choice of 6 possible shares which you can buy any quantity of. In each decision-making situation, you will receive an initial amount of 1,000 Taler to use as you wish.

You do not have to use the full amount of money to purchase shares. The portion not invested in shares will go directly into your final balance unchanged i.e. with no interest earned. You may buy different shares simultaneously. You may also choose to not buy any shares.

In every situation, you will first receive an overview of the price development of all 6 shares over the previous 6 periods.

To purchase shares, please enter the desired amount. The amount can be adjusted with the 2 circular buttons in the row of the respective share. If you would like to increase the amount, click the right circle ("increase"). If you would like to correct the amount you entered and would like to reduce the amount, then click on the left circle (“reduce”). Once you have reached your desired quantity of shares to purchase, click “buy”. Only then will your purchase be made. Please be aware that in every situation you only have 1,000 Taler available to you. You cannot borrow money. There are no additional costs when purchasing shares.

You make your purchase decision in Period 0. In the following period, Period 1, any shares you purchased are automatically sold.

2) Automatic Selling of Shares

At the end of every situation (i.e. in Period 1) all of your shares will be sold. Your final balance at the end of every situation is composed of the sum of the Taler you did not invest in shares and the value of your shares after Period 1.

On the next screen you will be shown the results of your investment. Click “next” to move on to the next decision situation.

Price development of company shares:

The price of a share can rise or fall from one period to the next. The 6 shares to choose from each contain different types of shares that have different probabilities to rise or fall per period:

Stock Type	Probability to Rise	Probability to Fall
++	65%	35%
+	55%	45%
0	50%	50%
0	50%	50%
−	45%	55%
−−	35%	65%

However, it is not disclosed which shares correspond to which share type. In each situation, the shares are arranged based on the initial price in the first period (in ascending order). Thus, the order of the shares given provides no information about the type of share price.

When a share increases in price, the price change per share is either +1 Taler, +3 Taler, +5 Taler, or +10 Taler. Each of these values is equally likely when there is an increase.

When a share decreases in price, the price change per share is either −1 Taler, −3 Taler, −5 Taler, or −10 Taler. Each of these values is equally likely when there is a decrease.

Be aware that the 10 decision situations are independent from each other. The share in each situation has no connection to the shares in the other situations. At the beginning of each situation, you will receive 1,000 Taler regardless of your results in the other situations.

On the next page you can get an idea of how to make your investment decision and which information will be made available to you.

A.7 Part 2. Final Questions

This part of the experiment is not relevant for your payout.

After the investment decisions have been made, you will be asked a few final questions. Please answer the questions. Please click "next" to confirm your answers and go to the next page.

Please stay in your seat until the experiment supervisor calls you forward for your payout for the experiment.

A.8 Determining Your Payment

Your payment depends on your decisions during the experiment. It is based on your final balance in Taler after you made your investments. In other words, it is the sum of your money not spent on buying shares from the initial 1,000 Taler plus the value of your shares after playing Period 1. However, your win or loss from investing activities (difference between buy price and sale price, if you invested) is doubled. Thus, the following calculations are made for each decision situation:

$$\text{Final Balance in Taler} = \text{Initial Balance in Taler} + 2 \times (\text{sell-price in Period 1} - \text{buy-price in Period 0 of the purchased shares in Taler})$$

One of your 10 decision situations from Part 1 will be chosen at random, the final balance of this situation will be paid to you (converted to €). So, you should try to maximize your balance in every decision-making situation.

The fixed conversion rate of 100 Taler to € 1 will be used to convert your balance. This conversion rate is the same for every subject. If you earned more Taler compared to other subjects, then you will also receive more € in comparison.

A.9 Sample Calculation per Period

Imagine that in Period 1 you invested in a company share that cost 50 Taler. You bought 20 shares. In Period 1 you discover that the value of the share increased at +3 Taler per share. This results in the following calculation:

$$\text{Final Balance} = 1,000 \text{ Taler} + 2 \times ((53 \times 20) - (50 \times 20)) = 1,120 \text{ Taler}$$

If the value had decreased, for example, -3 Taler per share, the following calculation would be made:

$$\text{Final Balance} = 1,000 \text{ Taler} + 2 \times ((47 \times 20) - (50 \times 20)) = 880 \text{ Taler}$$

A.10 Questionnaire

Please answer each of the following questions as accurately as possible. Of course your responses will be treated completely confidentially. Your answers will be of immense value for our scientific investigation. If you have any questions, do not hesitate to contact the experimenter. Thank you in advance for your cooperation.

A.10.1 Sociodemographics

1. What is your gender?

   ☐ Male

   ☐ Female

2. How old are you in years?

   Age in years: ☐

3. If you are a student, what is you major?

   ☐ Business Administration

   ☐ Economics

   ☐ Socioeconomics

   ☐ Other

4. What is the level of the highest degree you are currently studying?

   ☐ Qualification for university entrance

   ☐ Bachelor

   ☐ Master

   ☐ Doctor/PhD

   ☐ Other

5. How do you rate your your statistical knowledge?

☐ Basic knowledge (from school)

☐ Advanced knowledge (basic courses at the University)

☐ Deeper knowledge (specialized courses at the University)

☐ Other

A.10.2 Risk Preferences: Lottery Task

18. Here you see two lotteries each (option A and option B) with different outcomes and probabilities. Please indicate which of the both options you would prefer for *each* row.

Option A	Option B
1/10 of €2.00, and 9/10 of €1.60	1/10 of €3.85, and 9/10 of €0.10
2/10 of €2.00, and 8/10 of €1.60	2/10 of €3.85, and 8/10 of €0.10
3/10 of €2.00, and 7/10 of €1.60	3/10 of €3.85, and 7/10 of €0.10
4/10 of €2.00, and 6/10 of €1.60	4/10 of €3.85, and 6/10 of €0.10
5/10 of €2.00, and 5/10 of €1.60	5/10 of €3.85, and 5/10 of €0.10
6/10 of €2.00, and 4/10 of €1.60	6/10 of €3.85, and 4/10 of €0.10
7/10 of €2.00, and 3/10 of €1.60	7/10 of €3.85, and 3/10 of €0.10
8/10 of €2.00, and 2/10 of €1.60	8/10 of €3.85, and 2/10 of €0.10
9/10 of €2.00, and 1/10 of €1.60	9/10 of €3.85, and 1/10 of €0.10
10/10 of €2.00, and 0/10 of €1.60	10/10 of €3.85, and 0/10 of €0.10

A.10.3 Risk Preferences: Self-Assessment

19. How do you see yourself: are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?

☐ 0 (avoid taking risks)

☐ 1

☐ 2

☐ 3

☐ 4

☐ 5

☐ 6

☐ 7

☐ 8

☐ 9

☐ 10 (take risks)

☐ Refusal

A.10.4 Problems and Comments

20. Did you ever make a mistake during the investment task?

    If so, please tell us exactly what went wrong and in what period: ☐

21. Did you find the instructions of the experiment clear and understandable?

    What if anything was unclear? ☐

B Comprehension Questions

B.0.1 Question 1

From the instructions you could see that the price of the shares can rise or fall from one period to the next. With an equal probability, the price change per share assumes the values +/- 1, +/- 3, +/- 5 or +/- ☐ ?

B.0.2 Question 2

Please state which answer you believe is correct. The probability of a price increase for a company's share depends on:

☐ chance

☐ the type of share

☐ the investment decision in the previous decision-making situation

C Experimental Design

Table 8 shows the labels of the six stocks in each of the 10 choice sets of the experiment. Since subjects make 10 independent one-shot decisions, the labels change in each decision task.

Table 8: Experimental Design: Labels

This table displays the labels of the stocks used in the 10 choice sets of the experiment.

1	2	3	4	5	6	7	8	9	10
AA	BA	CA	DA	EA	FA	GA	HA	IA	JA
AB	BB	CB	DB	EB	FB	GB	HB	IB	JB
AC	BC	CC	DC	EC	FC	GC	HC	IC	JC
AD	BD	CD	DD	ED	FD	GD	HD	ID	JD
AE	BE	CE	DE	EE	FE	GE	HE	IE	JE
AF	BF	CF	DF	EF	FF	GF	HF	IF	JF

Table 9 summarizes the manipulations in each of the 10 choice sets. As an example, in the first choice set, Stock ++ is manipulated. While some subjects (control) observe this stock having a return of +1 in Period 0, others (treatment) observe the same sequence with the exception that the return of the stock in Period 0 is equal to +10. Note that with respect to the neutral stocks, one stock exhibits Period 0 returns comparable to the positive stocks while the other stock has Period 0 returns comparable to the negative stocks.

Table 9: Experimental Design: Magnitude of Price Changes

This table displays the stock which is manipulated in each of the 10 choice sets of the experiment as well as the magnitude of normal and extreme price changes in the period prior to the purchase decision.

Choice set	Manipulated stock	Normal	Extreme
1	++	+1	+10
2	++	+1	+10
3	+	+1	+10
4	+	+1	+10
6	0	+1	+10
5	0	-1	-10
7	−	-1	-10
8	−	-1	-10
9	−−	-1	-10
10	−−	-1	-10

D Choice Sets

Table 10: Experimental Design: Choice Sets 1–4

Choice Set 1																
	Control								Treatment							
Period	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**
Price Change	40	45 (+5)	48 (+3)	53 (+5)	56 (+3)	46 (-10)	47 (+1)	48 (+1)	40	45 (+5)	48 (+3)	53 (+5)	56 (+3)	46 (-10)	56 (+10)	57 (+1)
Price Change	45	40 (-5)	45 (+5)	46 (+1)	41 (-5)	46 (+5)	41 (-5)	40 (-1)	45	40 (-5)	45 (+5)	46 (+1)	41 (-5)	46 (+5)	41 (-5)	40 (-1)
Price Change	50	49 (-1)	46 (-3)	45 (-1)	35 (-10)	34 (-1)	35 (+1)	40 (+5)	50	49 (-1)	46 (-3)	45 (-1)	35 (-10)	34 (-1)	35 (+1)	40 (+5)
Price Change	55	50 (-5)	53 (+3)	63 (+10)	58 (-5)	53 (-5)	52 (-1)	42 (-10)	55	50 (-5)	53 (+3)	63 (+10)	58 (-5)	53 (-5)	52 (-1)	42 (-10)
Price Change	60	61 (+1)	62 (+1)	63 (+1)	73 (+10)	78 (+5)	77 (-1)	74 (-3)	60	61 (+1)	62 (+1)	63 (+1)	73 (+10)	78 (+5)	77 (-1)	74 (-3)
Price Change	65	75 (+10)	65 (-10)	68 (+3)	73 (+5)	72 (-1)	62 (-10)	61 (-1)	65	75 (+10)	65 (-10)	68 (+3)	73 (+5)	72 (-1)	62 (-10)	61 (-1)

Choice Set 2																
	Control								Treatment							
Period	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**
Price Change	40	35 (-5)	45 (+10)	50 (+5)	53 (+3)	58 (+5)	59 (+1)	58 (-1)	40	35 (-5)	45 (+10)	50 (+5)	53 (+3)	58 (+5)	68 (+10)	67 (-1)
Price Change	45	42 (-3)	45 (+3)	40 (-5)	37 (-3)	32 (-5)	42 (+10)	43 (+1)	45	42 (-3)	45 (+3)	40 (-5)	37 (-3)	32 (-5)	42 (+10)	43 (+1)
Price Change	50	40 (-10)	45 (+5)	48 (+3)	38 (-10)	39 (+1)	36 (-3)	46 (+10)	50	40 (-10)	45 (+5)	48 (+3)	38 (-10)	39 (+1)	36 (-3)	46 (+10)
Price Change	55	52 (-3)	49 (-3)	48 (-1)	38 (-10)	33 (-5)	32 (-1)	33 (+1)	55	52 (-3)	49 (-3)	48 (-1)	38 (-10)	33 (-5)	32 (-1)	33 (+1)
Price Change	60	57 (-3)	52 (-5)	42 (-10)	52 (+10)	55 (+3)	60 (+5)	50 (-10)	60	57 (-3)	52 (-5)	42 (-10)	52 (+10)	55 (+3)	60 (+5)	50 (-10)
Price Change	65	55 (-10)	54 (-1)	55 (+1)	54 (-1)	53 (-1)	48 (-5)	47 (-1)	65	55 (-10)	54 (-1)	55 (+1)	54 (-1)	53 (-1)	48 (-5)	47 (-1)

Choice Set 3																
	Control								Treatment							
Period	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**
Price Change	40	45 (+5)	42 (-3)	41 (-1)	51 (+10)	46 (-5)	41 (-5)	38 (-3)	40	45 (+5)	42 (-3)	41 (-1)	51 (+10)	46 (-5)	41 (-5)	38 (-3)
Price Change	45	50 (+5)	60 (+10)	59 (-1)	49 (-10)	46 (-3)	47 (+1)	48 (+1)	45	50 (+5)	60 (+10)	59 (-1)	49 (-10)	46 (-3)	56 (+10)	57 (+1)
Price Change	50	49 (-1)	54 (+5)	51 (-3)	52 (+1)	53 (+1)	52 (-1)	62 (+10)	50	49 (-1)	54 (+5)	51 (-3)	52 (+1)	53 (+1)	52 (-1)	62 (+10)
Price Change	55	52 (-3)	49 (-3)	50 (+1)	45 (-5)	42 (-3)	37 (-5)	27 (-10)	55	52 (-3)	49 (-3)	50 (+1)	45 (-5)	42 (-3)	37 (-5)	27 (-10)
Price Change	60	57 (-3)	56 (-1)	46 (-10)	45 (-1)	35 (-10)	30 (-5)	27 (-3)	60	57 (-3)	56 (-1)	46 (-10)	45 (-1)	35 (-10)	30 (-5)	27 (-3)
Price Change	65	62 (-3)	65 (+3)	75 (+10)	70 (-5)	75 (+5)	78 (+3)	68 (-10)	65	62 (-3)	65 (+3)	75 (+10)	70 (-5)	75 (+5)	78 (+3)	68 (-10)

Choice Set 4																
	Control								Treatment							
Period	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**
Price Change	40	43 (+3)	44 (+1)	34 (-10)	29 (-5)	24 (-5)	25 (+1)	24 (-1)	40	43 (+3)	44 (+1)	34 (-10)	29 (-5)	24 (-5)	25 (+1)	24 (-1)
Price Change	45	55 (+10)	60 (+5)	61 (+1)	60 (-1)	61 (+1)	62 (+1)	59 (-3)	45	55 (+10)	60 (+5)	61 (+1)	60 (-1)	61 (+1)	71 (+10)	68 (-3)
Price Change	50	47 (-3)	37 (-10)	32 (-5)	42 (+10)	39 (-3)	34 (-5)	39 (+5)	50	47 (-3)	37 (-10)	32 (-5)	42 (+10)	39 (-3)	34 (-5)	39 (+5)
Price Change	55	60 (+5)	61 (+1)	60 (-1)	57 (-3)	47 (-10)	52 (+5)	53 (+1)	55	60 (+5)	61 (+1)	60 (-1)	57 (-3)	47 (-10)	52 (+5)	53 (+1)
Price Change	60	50 (-10)	55 (+5)	56 (+1)	61 (+5)	64 (+3)	69 (+5)	79 (+10)	60	50 (-10)	55 (+5)	56 (+1)	61 (+5)	64 (+3)	69 (+5)	79 (+10)
Price Change	65	68 (+3)	63 (-5)	60 (-3)	55 (-5)	56 (+1)	59 (+3)	60 (+1)	65	68 (+3)	63 (-5)	60 (-3)	55 (-5)	56 (+1)	59 (+3)	60 (+1)

Table 11: Experimental Design: Choice Sets 5–8

Choice Set 5

	Control								Treatment							
Period	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**
Price	40	39	36	39	44	54	53	48	40	39	36	39	44	54	44	39
Change		(-1)	(-3)	(+3)	(+5)	(+10)	(-1)	(-5)		(-1)	(-3)	(+3)	(+5)	(+10)	(-10)	(-5)
Price	45	46	56	46	47	57	60	65	45	46	56	46	47	57	60	65
Change		(+1)	(+10)	(-10)	(+1)	(+10)	(+3)	(+5)		(+1)	(+10)	(-10)	(+1)	(+10)	(+3)	(+5)
Price	50	60	70	73	63	53	58	59	50	60	70	73	63	53	58	59
Change		(+10)	(+10)	(+3)	(-10)	(-10)	(+5)	(+1)		(+10)	(+10)	(+3)	(-10)	(-10)	(+5)	(+1)
Price	55	45	48	53	52	42	41	36	55	45	48	53	52	42	41	36
Change		(-10)	(+3)	(+5)	(-1)	(-10)	(-1)	(-5)		(-10)	(+3)	(+5)	(-1)	(-10)	(-1)	(-5)
Price	60	70	65	64	63	58	48	43	60	70	65	64	63	58	48	43
Change		(+10)	(-5)	(-1)	(-1)	(-5)	(-10)	(-5)		(+10)	(-5)	(-1)	(-1)	(-5)	(-10)	(-5)
Price	65	66	65	60	63	58	48	45	65	66	65	60	63	58	48	45
Change		(+1)	(-1)	(-5)	(+3)	(-5)	(-10)	(-3)		(+1)	(-1)	(-5)	(+3)	(-5)	(-10)	(-3)

Choice Set 6

	Control								Treatment							
Period	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**
Price	40	45	50	47	50	60	63	53	40	45	50	47	50	60	63	53
Change		(+5)	(+5)	(-3)	(+3)	(+10)	(+3)	(-10)		(+5)	(+5)	(-3)	(+3)	(+10)	(+3)	(-10)
Price	45	40	35	38	37	34	31	30	45	40	35	38	37	34	31	30
Change		(-5)	(-5)	(+3)	(-1)	(-3)	(-3)	(-1)		(-5)	(-5)	(+3)	(-1)	(-3)	(-3)	(-1)
Price	50	51	52	51	46	41	42	37	50	51	52	51	46	41	51	46
Change		(+1)	(+1)	(-1)	(-5)	(-5)	(+1)	(-5)		(+1)	(+1)	(-1)	(-5)	(-5)	(+10)	(-5)
Price	55	45	50	55	54	55	56	59	55	45	50	55	54	55	56	59
Change		(-10)	(+5)	(+5)	(-1)	(+1)	(+1)	(+3)		(-10)	(+5)	(+5)	(-1)	(+1)	(+1)	(+3)
Price	60	55	60	50	49	46	45	44	60	55	60	50	49	46	45	44
Change		(-5)	(+5)	(-10)	(-1)	(-3)	(-1)	(-1)		(-5)	(+5)	(-10)	(-1)	(-3)	(-1)	(-1)
Price	65	70	75	80	79	84	89	99	65	70	75	80	79	84	89	99
Change		(+5)	(+5)	(+5)	(-1)	(+5)	(+5)	(+10)		(+5)	(+5)	(+5)	(-1)	(+5)	(+5)	(+10)

Choice Set 7

	Control								Treatment							
Period	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**
Price	40	43	42	52	42	41	46	47	40	43	42	52	42	41	46	47
Change		(+3)	(-1)	(+10)	(-10)	(-1)	(+5)	(+1)		(+3)	(-1)	(+10)	(-10)	(-1)	(+5)	(+1)
Price	45	55	45	50	40	39	38	28	45	55	45	50	40	39	29	19
Change		(+10)	(-10)	(+5)	(-10)	(-1)	(-1)	(-10)		(+10)	(-10)	(+5)	(-10)	(-1)	(-10)	(-10)
Price	50	51	41	38	43	53	50	45	50	51	41	38	43	53	50	45
Change		(+1)	(-10)	(-3)	(+5)	(+10)	(-3)	(-5)		(+1)	(-10)	(-3)	(+5)	(+10)	(-3)	(-5)
Price	55	52	47	46	51	41	38	35	55	52	47	46	51	41	38	35
Change		(-3)	(-5)	(-1)	(+5)	(-10)	(-3)	(-3)		(-3)	(-5)	(-1)	(+5)	(-10)	(-3)	(-3)
Price	60	63	68	69	72	62	67	62	60	63	68	69	72	62	67	62
Change		(+3)	(+5)	(+1)	(+3)	(-10)	(+5)	(-5)		(+3)	(+5)	(+1)	(+3)	(-10)	(+5)	(-5)
Price	65	64	74	84	87	90	80	77	65	64	74	84	87	90	80	77
Change		(-1)	(+10)	(+10)	(+3)	(+3)	(-10)	(-3)		(-1)	(+10)	(+10)	(+3)	(+3)	(-10)	(-3)

Choice Set 8

	Control								Treatment							
Period	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**
Price	40	45	55	56	66	71	72	75	40	45	55	56	66	71	72	75
Change		(+5)	(+10)	(+1)	(+10)	(+5)	(+1)	(+3)		(+5)	(+10)	(+1)	(+10)	(+5)	(+1)	(+3)
Price	45	42	32	29	34	35	45	55	45	42	32	29	34	35	45	55
Change		(-3)	(-10)	(-3)	(+5)	(+1)	(+10)	(+10)		(-3)	(-10)	(-3)	(+5)	(+1)	(+10)	(+10)
Price	50	47	42	45	48	43	44	41	50	47	42	45	48	43	44	41
Change		(-3)	(-5)	(+3)	(+3)	(-5)	(+1)	(-3)		(-3)	(-5)	(+3)	(+3)	(-5)	(+1)	(-3)
Price	55	56	66	67	68	67	77	87	55	56	66	67	68	67	77	87
Change		(+1)	(+10)	(+1)	(+1)	(-1)	(+10)	(+10)		(+1)	(+10)	(+1)	(+1)	(-1)	(+10)	(+10)
Price	60	57	58	68	58	48	47	42	60	57	58	68	58	48	38	33
Change		(-3)	(+1)	(+10)	(-10)	(-10)	(-1)	(-5)		(-3)	(+1)	(+10)	(-10)	(-10)	(-10)	(-5)
Price	65	62	57	58	57	56	53	52	65	62	57	58	57	56	53	52
Change		(-3)	(-5)	(+1)	(-1)	(-1)	(-3)	(-1)		(-3)	(-5)	(+1)	(-1)	(-1)	(-3)	(-1)

Table 12: Experimental Design: Choice Sets 9–10

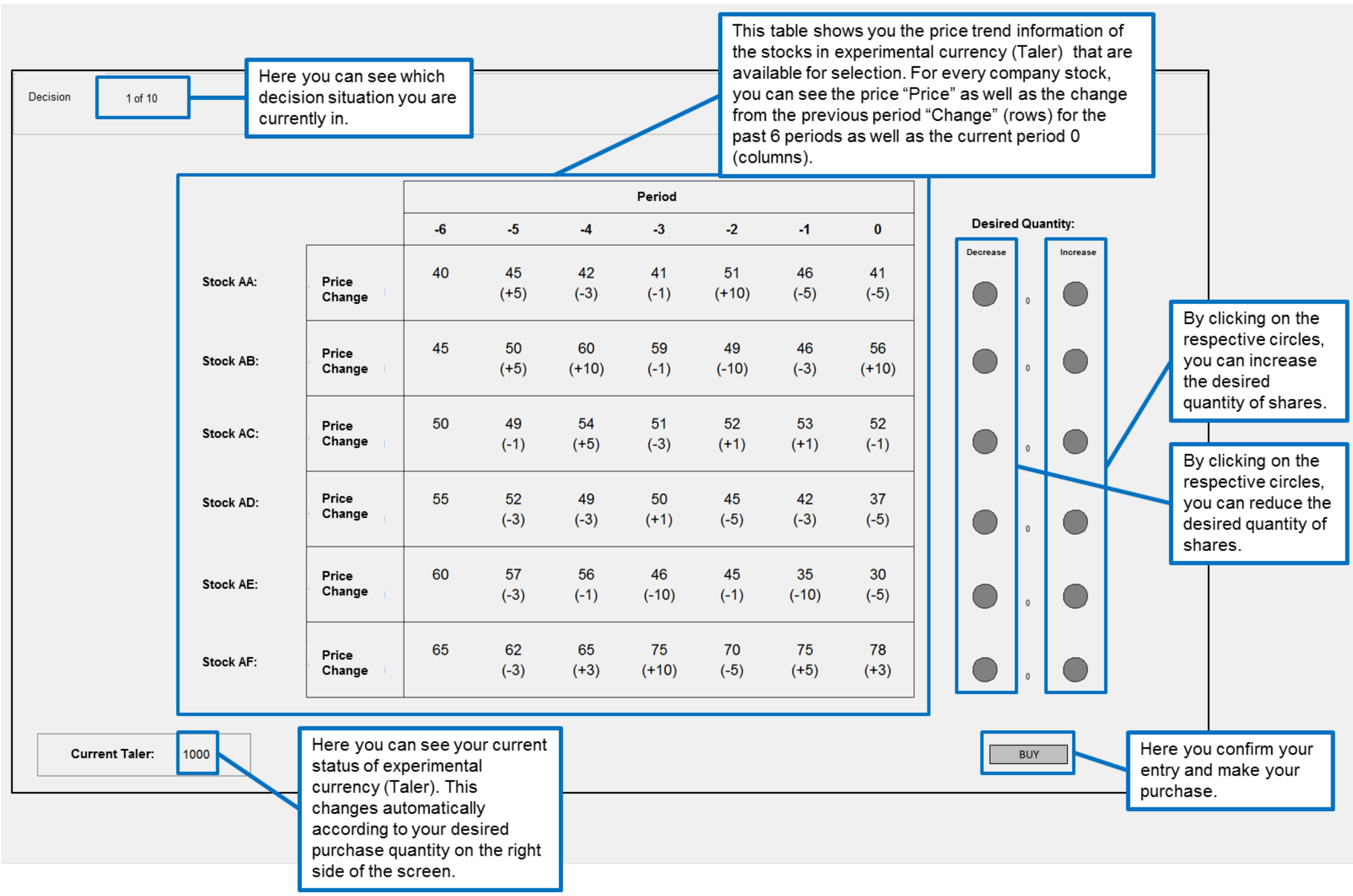
Choice Set 9																
	Control								Treatment							
Period	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**
Price Change	40	45 (+5)	44 (-1)	43 (-1)	40 (-3)	30 (-10)	25 (-5)	30 (+5)	40	45 (+5)	44 (-1)	43 (-1)	40 (-3)	30 (-10)	25 (-5)	30 (+5)
Price Change	45	50 (+5)	49 (-1)	59 (+10)	60 (+1)	70 (+10)	73 (+3)	74 (+1)	45	50 (+5)	49 (-1)	59 (+10)	60 (+1)	70 (+10)	73 (+3)	74 (+1)
Price Change	50	47 (-3)	50 (+3)	47 (-3)	57 (+10)	62 (+5)	59 (-3)	49 (-10)	50	47 (-3)	50 (+3)	47 (-3)	57 (+10)	62 (+5)	59 (-3)	49 (-10)
Price Change	55	60 (+5)	61 (+1)	62 (+1)	67 (+5)	62 (-5)	61 (-1)	56 (-5)	55	60 (+5)	61 (+1)	62 (+1)	67 (+5)	62 (-5)	61 (-1)	56 (-5)
Price Change	60	57 (-3)	58 (+1)	57 (-1)	47 (-10)	42 (-5)	37 (-5)	36 (-1)	60	57 (-3)	58 (+1)	57 (-1)	47 (-10)	42 (-5)	37 (-5)	36 (-1)
Price Change	65	66 (+1)	61 (-5)	56 (-5)	46 (-10)	41 (-5)	40 (-1)	39 (-1)	65	66 (+1)	61 (-5)	56 (-5)	46 (-10)	41 (-5)	31 (-10)	30 (-1)

Choice Set 10																
	Control								Treatment							
Period	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**
Price Change	40	39 (-1)	38 (-1)	35 (-3)	45 (+10)	50 (+5)	47 (-3)	57 (+10)	40	39 (-1)	38 (-1)	35 (-3)	45 (+10)	50 (+5)	47 (-3)	57 (+10)
Price Change	45	42 (-3)	32 (-10)	42 (+10)	52 (+10)	49 (-3)	54 (+5)	59 (+5)	45	42 (-3)	32 (-10)	42 (+10)	52 (+10)	49 (-3)	54 (+5)	59 (+5)
Price Change	50	47 (-3)	52 (+5)	62 (+10)	63 (+1)	62 (-1)	67 (+5)	68 (+1)	50	47 (-3)	52 (+5)	62 (+10)	63 (+1)	62 (-1)	67 (+5)	68 (+1)
Price Change	55	58 (+3)	63 (+5)	73 (+10)	83 (+10)	86 (+3)	89 (+3)	99 (+10)	55	58 (+3)	63 (+5)	73 (+10)	83 (+10)	86 (+3)	89 (+3)	99 (+10)
Price Change	60	50 (-10)	55 (+5)	52 (-3)	42 (-10)	41 (-1)	40 (-1)	30 (-10)	60	50 (-10)	55 (+5)	52 (-3)	42 (-10)	41 (-1)	31 (-10)	21 (-10)
Price Change	65	66 (+1)	56 (-10)	51 (-5)	61 (+10)	60 (-1)	57 (-3)	56 (-1)	65	66 (+1)	56 (-10)	51 (-5)	61 (+10)	60 (-1)	57 (-3)	56 (-1)

E Screenshots of Experimental Screen

Figure 4: Experimental Screen

This figure displays the experimental screen. The explanations provided in this screenshot were also available to subjects before the experiment was started.



F Tests of Robustness and Extensions

This section presents alternative specifications of our main regression displayed in Table 3.

Table 13 uses an alternative definition of the volume of shares purchased. Instead of using the number of stocks purchased as the dependent variable, the product of quantity and price is chosen. Our main results are qualitatively unchanged: significantly positive coefficients of extreme prior returns are observed in the cross-section and for the subset of negative manipulated stocks. As expected, the coefficients are larger in size since the product of stock quantity and price is chosen as the dependent variable.

Table 13: Extreme Returns and Volume of Shares Purchased

This table contains the coefficients and t-statistics (in parentheses) of OLS regressions in which the dependent variable is the volume of shares purchased, defined as the product of quantity and price. *Extreme prior return* represents a dummy variable which is equal to one if the return of the treated stock in the period preceding the purchase decision (Period 0) is extremely high or low (i.e., equal to 10 in absolute size); *Risk tolerance* is subjects' self-assessed risk tolerance in the general domain, measured on a scale from 0 (lowest) to 10 (highest); *Age* is subjects' age, measured in years; *Male* is a dummy variable which is equal to one if a subject is male; *Earnings in preceding decision* denotes the amount of Taler a subject earned in the preceding decision situation; *Number of decision* denotes the number of the respective decision for a subject (ranging from 1 to 10); *Session* is a dummy variable representing the different sessions of the experiment; *Rank of extreme prior return* is a dummy variable indicating whether the extreme prior return of the treated stock is a unique maximum or minimum; *Degree* is the degree with which a subject expects to graduate; *Field of study* represents subjects' main field of study; *Statistics knowledge* is subjects' self-assessed knowledge in statistics. Standard errors are clustered at the subject level. *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) All Choice Sets	(2) CS 1-4 (positive)	(3) CS 5&6 (neutral)	(4) CS 7-10 (negative)
Extreme prior return	22.779**	16.451	20.979	23.564**
	(2.13)	(0.86)	(1.03)	(2.35)
Risk tolerance	10.267***	11.897**	6.490**	10.268
	(2.86)	(2.27)	(2.34)	(1.42)
Age	-3.358***	-7.730***	-2.784**	0.903
	(-3.09)	(-2.77)	(-2.18)	(0.68)
Male	36.242**	86.144***	16.226	-5.678
	(2.38)	(2.81)	(1.12)	(-0.21)
Earnings in preceding decision	0.009	0.008	-0.040	-0.005
	(0.56)	(0.21)	(-1.16)	(-0.43)
Number of decision	0.421	-1.195	-4.155	2.234
	(0.21)	(-0.34)	(-1.51)	(0.91)
Constant	119.152***	335.659***	173.027***	-46.891
	(2.76)	(3.73)	(2.68)	(-0.73)
Session	Yes	Yes	Yes	Yes
Rank of extreme prior return	Yes	Yes	Yes	Yes
Degree	Yes	Yes	Yes	Yes
Field of study	Yes	Yes	Yes	Yes
Statistics knowledge	Yes	Yes	Yes	Yes
N	1,170	468	234	468
R^2	0.07	0.15	0.14	0.09

Table 14 shows the results of a Tobit regression in which the dependent variable is equal to the number of shares purchased. The dependent variable is left-censored at zero. Compared to our main specification, the results are qualitatively unchanged. Note that the coefficients of extreme prior returns are significant at the 1% level both in the cross-section and for negative stocks.

Table 14: Extreme Returns and Number of Shares Purchased (Tobit Specification)

This table contains the coefficients and t-statistics (in parentheses) of Tobit regressions in which the dependent variable is the number of shares purchased. *Extreme prior return* represents a dummy variable which is equal to one if the return of the treated stock in the period preceding the purchase decision (Period 0) is extremely high or low (i.e., equal to 10 in absolute size); *Risk tolerance* is subjects' self-assessed risk tolerance in the general domain, measured on a scale from 0 (lowest) to 10 (highest); *Age* is subjects' age, measured in years; *Male* is a dummy variable which is equal to one if a subject is male; *Earnings in preceding decision* denotes the amount of Taler a subject earned in the preceding decision situation; *Number of decision* denotes the number of the respective decision for a subject (ranging from 1 to 10); *Session* is a dummy variable representing the different sessions of the experiment; *Rank of extreme prior return* is a dummy variable indicating whether the extreme prior return of the treated stock is a unique maximum or minimum; *Degree* is the degree with which a subject expects to graduate; *Field of study* represents subjects' main field of study; *Statistics knowledge* is subjects' self-assessed knowledge in statistics. Standard errors are clustered at the subject level. *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) All Choice Sets	(2) CS 1-4 (positive)	(3) CS 5&6 (neutral)	(4) CS 7-10 (negative)
Extreme prior return	1.250***	0.070	1.308	3.593***
	(2.60)	(0.16)	(1.52)	(2.65)
Risk tolerance	0.343**	0.211*	0.246	0.752
	(2.24)	(1.65)	(1.45)	(1.40)
Age	-0.119***	-0.172***	-0.144	0.056
	(-2.80)	(-2.69)	(-1.58)	(0.31)
Male	0.362	1.392**	0.235	-2.130
	(0.58)	(2.09)	(0.30)	(-0.95)
Earnings in preceding decision	0.000	0.000	-0.002	-0.000
	(0.32)	(0.53)	(-1.50)	(-0.10)
Number of decision	0.021	0.007	-0.173	0.105
	(0.27)	(0.10)	(-1.26)	(0.51)
Constant	-0.412	4.918**	3.872	-12.080
	(-0.21)	(2.25)	(1.17)	(-1.56)
Session	Yes	Yes	Yes	Yes
Rank of extreme prior return	Yes	Yes	Yes	Yes
Degree	Yes	Yes	Yes	Yes
Field of study	Yes	Yes	Yes	Yes
Statistics knowledge	Yes	Yes	Yes	Yes
N	1,170	468	234	468
Pseudo R^2	0.02	0.03	0.05	0.04

The following analyses are restricted to choice sets with positive and negative manipulated stocks in the second row of the information table provided to the subjects. Table 15 shows the results of an OLS regression in which the dependent variable is subjects' relative fixation duration on the manipulated stock AOI. The main explanatory variable is our treatment dummy variable. The results show that although positively and negatively manipulated stocks are shown in the same row, extreme returns significantly increase visual attention to negative stocks, but not to positive stocks. We control for subjects' risk tolerance, age, gender, earnings in the preceding decision, number of decision, education, field of study, statistics knowledge, as well as the experimental session and whether the extreme prior return of the treated stock represents a unique maximum or minimum

Table 15: Extreme Returns and Relative Fixation Durations for Same Row Stocks

This table contains the coefficients and t-statistics (in parentheses) of OLS regressions in which the dependent variable is subjects' relative fixation duration on the manipulated stock AOI relative to the fixation duration on all stock AOIs for each choice set in percent. *Extreme prior return* represents a dummy variable which is equal to one if the return of the treated stock in the period preceding the purchase decision (Period 0) is extremely high or low (i.e., equal to 10 in absolute size); *Risk tolerance* is subjects' self-assessed risk tolerance in the general domain, measured on a scale from 0 (lowest) to 10 (highest); *Age* is subjects' age, measured in years; *Male* is a dummy variable which is equal to one if a subject is male; *Earnings in preceding decision* denotes the amount of Taler a subject earned in the preceding decision situation; *Number of decision* denotes the number of the respective decision for a subject (ranging from 1 to 10); *Session* is a dummy variable representing the different sessions of the experiment; *Rank of extreme prior return* is a dummy variable indicating whether the extreme prior return of the treated stock is a unique maximum or minimum; *Degree* is the degree with which a subject expects to graduate; *Field of study* represents subjects' main field of study; *Statistics knowledge* is subjects' self-assessed knowledge in statistics. Standard errors are clustered at the subject level. *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) CS 3,4,7 (all)	(2) CS 3,4 (positive)	(3) CS 7 (negative)
Extreme prior return	0.026*	0.016	0.053*
	(1.79)	(0.89)	(1.89)
Risk tolerance	0.001	0.002	0.002
	(0.44)	(0.62)	(0.30)
Age	-0.002	-0.002	-0.001
	(-1.34)	(-1.14)	(-0.15)
Male	0.003	0.010	-0.004
	(0.20)	(0.58)	(-0.15)
Earnings in preceding decision	-0.000	-0.000	0.000
	(-0.15)	(-1.40)	(1.14)
Number of decision	0.004	0.005	0.005
	(1.34)	(1.40)	(1.01)
Constant	0.314***	0.392***	0.141
	(5.99)	(5.41)	(1.05)
Session	Yes	Yes	Yes
Rank of extreme prior return	No	No	No
Degree	Yes	Yes	Yes
Field of study	Yes	Yes	Yes
Statistics knowledge	Yes	Yes	Yes
N	342	228	114
R^2	0.09	0.15	0.11

among all prior returns.

Table 16 shows results of additional regression analyses to those in Section 4.1.1. We ran the regression analyses with an alternative control variable capturing whether subjects follow a buying strategy in line with a belief in mean reversion across all ten decisions.

Figure 5 displays the results of our mediation analyses in Section 4.2.2 with a control variable capturing whether subjects follow a buying strategy in line with a belief in mean reversion. We use a dummy variable which is equal to one if the subject invested in a stock (other than the manipulated stock) with a prior negative return in the respective decision situation.

Table 16: Extreme Returns and Number of Shares Purchased with Control for Beliefs in Mean Reversion across Decisions

This table contains the coefficients and t-statistics (in parentheses) of OLS regressions in which the dependent variable is the number of shares of the manipulated stock (treatment or control) purchased. *Extreme prior return* represents a dummy variable which is equal to one if the return of the treated stock in the period preceding the purchase decision (Period 0) is extremely high or low (i.e., equal to 10 in absolute size); *Risk tolerance* is subjects' self-assessed risk tolerance in the general domain, measured on a scale from 0 (lowest) to 10 (highest); *Age* is subjects' age, measured in years; *Male* is a dummy variable which is equal to one if a subject is male; *Earnings in preceding decision* denotes the amount of Taler a subject earned in the preceding decision situation; *Number of decision* denotes the number of the respective decision for a subject (ranging from 1 to 10); *Number invests in other neg. return stock* is the control variable for beliefs in mean reversion, denoting the number of subject's investments in a stock (other than the manipulated stock) with a prior negative return across all decisions; *Session* is a dummy variable representing the different sessions of the experiment; *Rank of extreme prior return* is a dummy variable indicating whether the extreme prior return of the treated stock is a unique maximum or minimum; *Degree* is the degree with which a subject expects to graduate; *Field of study* represents subjects' main field of study; *Statistics knowledge* is subjects' self-assessed knowledge in statistics. Standard errors are clustered at the subject level. *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) All Choice Sets	(2) CS 1-4 (positive)	(3) CS 5&6 (neutral)	(4) CS 7-10 (negative)
Extreme prior return	0.445*	-0.083	0.469	0.913***
	(1.95)	(-0.25)	(1.15)	(2.65)
Risk tolerance	0.221**	0.238**	0.105*	0.255
	(2.55)	(2.52)	(1.78)	(1.27)
Age	-0.053**	-0.135***	-0.050*	0.034
	(-2.56)	(-3.06)	(-1.94)	(0.95)
Male	0.681**	1.402***	0.417	0.049
	(1.99)	(2.82)	(1.53)	(0.06)
Earnings in preceding decision	0.000	0.000	-0.001	0.000
	(0.22)	(0.34)	(-1.00)	(0.01)
Number of decision	0.029	-0.002	-0.073	0.065
	(0.63)	(-0.03)	(-1.30)	(0.79)
Number invests in other neg. return stock	0.073	-0.180**	0.159***	0.278***
	(1.63)	(-2.19)	(2.71)	(4.23)
Constant	1.418	6.281***	2.480*	-2.994
	(1.34)	(4.01)	(1.67)	(-1.41)
Session	Yes	Yes	Yes	Yes
Rank of extreme prior return	Yes	Yes	Yes	Yes
Degree	Yes	Yes	Yes	Yes
Field of study	Yes	Yes	Yes	Yes
Statistics knowledge	Yes	Yes	Yes	Yes
N	1,170	468	234	468
R^2	0.07	0.15	0.17	0.13

Figure 5: The Effect of Extreme Returns on Purchase Volume Through Visual Attention

This figure displays unstandardized regression coefficients from mediation analysis obtained through bootstrapping. The range in brackets represents the bias-corrected CI of the natural indirect effect. We control for risk tolerance, age, gender, subjects' earnings in the preceding decision, the number of the decision, and the ranking of the extreme return, and subjects' belief in mean reversion.