The Portfolio Composition Effect*

Jan Müller-Dethard, Martin Weber, and Pascal Kieren

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Abstract

This study asks whether a simple, counting-based measure of performance, which is the fraction of winner stocks in a portfolio, affects willingness to invest in the portfolio. We find experimental evidence that indicates that individuals allocate larger investments to portfolios with larger fractions of winner stocks, albeit alternative portfolios have *realized* identical overall portfolio returns and show identical *expected* risk-return characteristics. Building on our experimental findings, we show empirically that the proposed composition measure also matters for the demand of leading equity market index funds. A framework which combines category-based thinking and mental accounting can explain the effect.

Keywords: *Portfolio composition, investment behavior, categorical thinking, mental accounting.*

JEL classifications: *G11, G12, G40, D84.*

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Jan Müller-Dethard is at the University of Mannheim, Finance Department, L9, 1-2, D-68161 Mannheim, Germany, mueller-dethard@bank.bwl.uni-mannheim.de (corresponding author). Martin Weber is at the University of Mannheim, Finance Department, L9, 1-2, D-68161 Mannheim, Germany, weber@bank.bwl.uni-mannheim.de, and CEPR, London. Pascal Kieren is at Heidelberg University, Department of Economics, Bergheimer Straße 58, D-69115 Heidelberg, Germany, pascal.kieren@awi.uni-heidelberg.de.

Introduction

How do investors evaluate portfolios of stocks and what determines their investment decisions on the portfolio level? Much of the empirical and theoretical work on behavior focuses on individual assets. In particular, there exists much evidence on how people evaluate and trade *single stocks*, how investors form return expectations about *a given stock*, and how they evaluate *its* risk.[1] Even though these studies consistently show that investors do not form optimal portfolios, the portfolio is a relevant and important component to investor behavior: Hartzmark (2015) shows that the fact that stocks are part of a portfolio impacts how people build consideration sets which in turn affects how they evaluate and trade stocks. An, Engelberg, Henriksson, Wang, & Williams (2019) find that portfolio-level information matters to investors as the portfolio value affects stock selling behavior.

However, given that most investors hold a portfolio of stocks, it is somehow surprising that relatively little attention has been drawn to the role of the portfolio for investment behavior. In particular, it is unclear how people evaluate the *portfolio as a whole* and what parameters determine how they allocate funds across portfolios. For both theory and empirical analysis, it is important to know which determinants affect beliefs, preferences, and investment decisions not only on the level of the individual stock, but also on the level of the entire portfolio.

Prior literature has shown that investors track and evaluate the performance of stocks in their portfolio by constructing a set of investment episodes (i.e., mental accounts), whereby the sign of the outcome (gain or loss) plays a key role when evaluating the success of an investment episode (Barberis & Xiong, 2012; Frydman, Hartzmark & Solomon, 2017). On the portfolio level, this form of stock-by-stock accounting in a portfolio over time and across portfolios. For example, while one portfolio may primarily consist of good investment episodes, another similar portfolio may mainly consist of bad investment episodes, although both portfolios overall achieved the same return. In this paper, we examine exactly this relation. We ask whether the composition of winner and loser stocks in a portfolio has a causal effect on how people evaluate a portfolio and on how much money they are willing to invest in a portfolio.

In a series of experimental studies, we document a new stylized fact about how individuals evaluate portfolios and how they allocate funds across portfolios: the willingness to

[1] stock trading behavior, various studies show a substantial divergence between what standard finance theory implies and how people actually behave (Odean, 1998; Barber & Odean, 2000, 2008, 2013; Benartzi & Thaler, 2001).
such as base-rate neglect, prior-biased inference, overconfidence, and over-extrapolation from recent signals (see Benjamin, 2019 for a recent review).

r stocks. For two portfolios with the same realized and expected overall return and risk, people allocate significantly more funds to the portfolio with a larger fraction of winner stocks than to an alternative portfolio with a larger fraction of loser stocks. We then show that this difference in investment cannot be driven by differences in subjective beliefs about expected portfolio returns and volatility. Motivated by our experimental results, we turn to financial market data and examine whether the fraction of winner stocks matters not only for individual investment decisions in an experimental setting, but also for the demand of leading equity market index funds. If portfolio composition also plays a role for equity market index funds, we expect a positive relation between the fraction of winner members in an index and the subsequent fund inflows. We show evidence in favor of this.

Why should the composition of winner and loser stocks in a portfolio matter in the first place? Literature in cognitive psychology suggests people care about the fraction of stocks with positive returns in their portfolios. This suggestion is two-fold and extends the common framework of stock-by-stock mental accounting (Barberis & Xiong, 2012; Frydman et al., 2017) as follows: It assumes that investors think about performance in terms of categories

evaluate these categories based on the number of stocks they assign to each category, effectively using a counting heuristic. Both arguments can be grounded in the literature.

First, various studies in psychology show that categorical thinking is one of the strongest tendencies of humans (Rosch & Lloyd, 1978; Mervis & Rosch, 1981; Wilson & Keil, 1999). Adapted to finance, Barberis & Shleifer (2003) use this idea as the basis for a behavioral theory of co-movement for which Barberis, Shleifer, and Wurgler (2005) find confirming evidence. Barberis & Xiong (2012) use the notion of categories for a theory of realization utility and argue that people think about stocks in terms of good and bad investment episodes.

Second, there is literature rooted in psychology showing that people tend to use simplifying decision procedures and heuristics (e.g., rules of thumb, mental short-cuts) to cope with complex decision problems. For example, people use tallying strategies in which they simply count the number of cues favoring one alternative in comparison to others when they trade off options (Dawes, 1979; Rieskamp & Hoffrage, 1999; Gigerenzer & Gaissmaier, 2011). Applied to finance, Ungeheuer and Weber (2021) find that people evaluate dependence between stock returns as if they count the number of co-movements and thereby ignore the magnitude of returns. Applied to accounting, Koonce and Lipe (2017) demonstrate that investors use a counting heuristic to evaluate firm performance by counting the number of beats and misses of earnings benchmarks. In line with the idea that people use a counting heuristic, both studies suggest that there are situations in which investors might care first and foremost about the sign of a risky outcome rather than its actual size.

Motivated by this evidence, we develop a conceptual framework that combines category-based thinking and mental accounting to derive predictions on how people evaluate portfolios of stocks (Rosch & Lloyd, 1978; Thaler, 1999; Shefrin & Statman, 1987). As starting point, investors assign stocks to individual mental accounts, whereby they are reluctant to integrate outcomes across different accounts (Frydman et al., 2017). However, once they evaluate a whole portfolio, and are presented with all information together, they deviate from this strong form of narrow framing and complement the evaluation of individual stock outcomes with portfolio-level information. This means, they assign stocks

the complexity of full

different mental accounts, they simply engage in a counting heuristic to evaluate a portfolio investment decision. That is, they count the number of mental accounts (i.e., stocks) which are assigned either to

and effectively evaluate portfolios based on their fraction of winner and loser stocks rather than their overall expected return and variance.

To test predictions from this framework, we design a setting where portfolios with different fractions of winners, different overall returns, and different amounts of performance information can be exogenously assigned to subjects, their investment decisions and beliefs can be cleanly elicited, and a normative benchmark for learning can be established. We conduct a series of controlled experiments in which more than 1,300 subjects have to make several portfolio investment decisions. First, we show that the documented effect exists in an arguably simple investment task in which *realized* portfolio returns are identical. Within our baseline experimental scenario, individuals invest on average 26% (22%) more of their endowment in a portfolio which consists of 70% winner/30% loser stocks than in an alternative portfolio with identical realized positive (negative) return, but the reversed composition of 30% winner/70% loser stocks. Participants are also more optimistic in their return expectations and report lower risk evaluations for those portfolios which consist of more winner than loser stocks.

Second, we explore the channel underlying the effect by introducing a transparent and simple learning environment which allows subjects to infer the underlying quality of stocks in the portfolios from return realizations they observe. By doing so, we establish a benchmark for beliefs about *expected* returns and variance against which we can compare actual beliefs. In particular, we test whether the effect still persists if portfolios are generated in a way such that they are identical not only with respect to realized returns, but also with respect to expected returns and variance. Under this design modification, we rerun the baseline experiment. Yet, we find a strong portfolio composition effect among those participants who state the same beliefs about expected returns.

Finally, we put the effect to a severe test. This means, we (i) extent the learning phase prior to the investment decision, (ii) provide computational support for the calculation of expected returns, and (iii) clearly display both, the resulting expected returns as well as the variance of each portfolio. Importantly, we design portfolios in a way that there is a unique mean-variance efficient allocation which suggests an equal split of wealth between portfolios. We find that e

which results in a mean-variance suboptimal allocation. Compared to the baseline result, the effect gets stronger with a 43% larger investment of the endowment in the 70% winner/30% loser portfolio relative to the alternative portfolio with identical realized and expected return as well as variance, but the reversed fraction of winner stocks.

d variance can be ruled out as driving force, and as such it is not predicted by theories that assume mean-variance efficient portfolio selection (Markowitz, 1952). Importantly, we demonstrate that the portfolio composition effect cannot be explained by theories which assume either narrow-framing (stock-by-stock accounting) or broad framing (accounting based on the overall portfolio value) in isolation (e.g. Barberis & Xiong, 2012; Frydman et al., 2017).

In a final step, we apply our findings on the evaluation of portfolios from a controlled experimental setting to financial market data. In particular, we investigate whether historical fund flows of leading equity market index funds for the period 2010-2019 are affected by the

on of winner and loser members. Leading equity market indices represent ideal portfolio settings to test our hypothesis as they resemble relatively stable and transparent pre-

ket indices

capture a lot of attention in the media and press of the respective country since they are often

We find that the fraction of winner stocks of an index on a given day is positively related to fund flows on the subsequent two days. Across all leading equity market indices in our sample, we estimate that a portfolio composition of 100% winner stocks leads on average to roughly 0.5 million dollars higher inflows on the subsequent two days than a portfolio composition of 50% winner and 50% loser stocks, controlling for the index return. Several robustness analyses show that the effect is of rather short-term, daily nature, does not crucially depend on the tails of the fraction of winner distribution, and persists when controlling for the skewness of the stock returns of the index members. In essence, the effect manifests itself not just in the lab, but also in international equity market indices.

This paper contributes to several strands of literature. First, we contribute to theoretical and empirical research on the role of the portfolio for household and retail investor stock trading behavior in financial markets. On the theory front, the most promising models on how investors actually trade stocks in a portfolio rely on mental accounting (Thaler, 1985, 1999). Instead of total wealth and correlations, individuals track and evaluate performance by forming a set of investment episodes (Barberis & Xiong, 2012; Ingersoll & Jin, 2013). However, how investors construct and evaluate these investment episodes *over time* and *across assets* in a portfolio is still relatively unexplored. In the time dimension, Frydman et al. (2017) find evidence that suggests that mental accounts are not necessarily closed once a stock is sold. Instead, their findings suggest that mental accounts are rolled over from one asset into a new asset if the proceeds from the sale are reinvested within a short *period of time*. Our findings complement the rules underlying temporal mental accounting in another dimension the cross section. While investors are assumed to assign stocks to distinct mental accounts, which are then assumed to be evaluated in isolation from one another, we show that the individual account balances *across mental accounts* play a role when individuals evaluate a portfolio of stocks. As such, our findings suggest that the assumption of narrowly framed, stock-specific outcomes, as used in many models of temporal mental accounting and portfolio choice, does not necessarily imply that investors consider stocks in a portfolio in isolation, so to say, completely detached from one another. Instead, the composition of positive and negative account balances across stocks matters to investors and affects their portfolio performance evaluation. This suggestion is in line with Hartzmark (2015) who shows that investors trade stocks differently depending on how the other stocks in the portfolio perform (i.e., the rank effect). The basis of his reasoning is that sorting stocks by return is an intuitive way for how people evaluate stocks in their portfolio. On the portfolio level, our paper proposes that an even easier way to sort stocks in a portfolio is by sign. That means, when evaluating the performance of a portfolio, investors intuitively sort stocks into one of two categories: a winner (gain) category versus a loser (loss) category.

Second, we also contribute to the literature that examines how different levels of information in a portfolio (individual-stock level versus portfolio level) affect investor behavior. So far, most analyses of actual trading behavior focus on individual assets and thereby ignore how portfolio-level information affects trading. The first paper which takes a step in this direction is An et al.

selling behavior (e.g., the portfolio-driven disposition effect). While the focus of our paper is on the overall portfolio level rather than the individual stock level, our findings suggest that a crucial determinant for

composition of winner and loser stocks. We provide evidence that investors evaluate the overall

. Then, however, if the overall portfolio value affects stock trading and the fraction of winner stocks affects the overall portfolio evaluation, it may in turn be likely that the fraction of winner stocks indirectly also affects how investors trade individual stocks in their portfolios.

Third, we also contribute to a broader empirical literature on investor behavior. The main focus in the literature, by and large, has been on the asset class of individual stocks (Odean, 1998; Barber & Odean, 2000, 2001, 2008, 2013; Grinblatt & Keloharju, 2001; Feng & Seasholes, 2005).[2] More recently, studies started to investigate the selling behavior of investors in and across asset classes other than single stocks, such as equity mutual funds and index funds (Calvet, Campbell, & Sodini, 2009; Boldin & Cici, 2010; Chang, Solomon, & Westerfield, 2016; Bhattacharya, Loos, Meyer, & Hackethal, 2017). Given that more and more people invest in funds, which per definition also present portfolios, it becomes important to examine how investors evaluate portfolios and choose among them. Our findings suggest that the performance of the individual components plays an important role for the overall evaluation and choice of a portfolio. This is interesting since investors cannot change the holdings of mutual or index funds, but the performance of the individual holdings can ultimately affect whether to invest in a fund or not.

Forth, our findings contribute to theoretical and empirical work on how investors from beliefs about portfolios of stocks and on how they evaluate risk in a portfolio (i.e. how preferences are defined which investors use to evaluate risky outcomes). On the individual asset level, there is much evidence on how investors incorporate new information when forming

less evidence exists on how investors form beliefs about a portfolio of stocks. In particular, it

[2] Besides stocks, trading behavior has been examined for executive stock options (Heath, Huddart, & Lang, 1999), real estate (Genesove & Mayer, 2001), and online betting (Hartzmark & Solomon, 2012).

is unclear whether well-known findings on the individual asset level from experiments and surveys (e.g. return extrapolation) generalize to the overall portfolio level. We add to this literature by providing evidence that indicates that return extrapolation on the individual stock level aggregates to the overall portfolio level. Our findings suggest that a larger fraction of winner stocks in a portfolio is related to more optimistic return expectations for the portfolio. Moreover, we find a positive relation between the fraction of loser stocks of a portfolio and investors

Lichtenstein (1968), Anzoni and Zeisberger (2017), Holzmeister et al. (2020) and Zeisberger (2020), who propose and test alternative risk measures .
For portfolios of stocks, our findings are consistent with the idea that individuals use the fraction of loser stocks of a portfolio as an indicator for the ability of loss. Finally, we also contribute to the literature on risk preference specifications, narrow framing and aggregate stock market phenomena (Barberis, Huang & Santos, 2001; Barberis & Huang, 2001; Barberis, Huang & Thaler, 2006; Barberis, Mukherjee & Wang, 2016). In particular, our results provide experimental evidence for some of the common assumptions made in these models on how narrowly investors frame gains and losses in their portfolios. As proposed by Barberis and Huang (2001), our results suggest that a combination of a narrowly framed (stock-by-stock accounting) and a broadly framed (portfolio accounting) risk preference specification most likely fits best to how individuals actually evaluate risk in their portfolios.

The remainder of the paper is structured as follows. First, we design a conceptual framework of how investors evaluate portfolios and link it to how performance information is displayed in the field. Second, we provide experimental evidence of the portfolio composition effect and demonstrate that theories which either assume narrow framing or broad framing in isolation cannot account for such a finding. Third, we apply the insights from our experiments to financial market data. Finally, we discuss the implications of the effect and conclude.

1. Conceptual Framework and Portfolio Composition in the Field

A. A Counting-Based Framework of Portfolio Evaluation

The evaluation of portfolio investment decisions is complex. Investors are faced with much information and should if they take normative advice solve an optimization problem (Markowitz, 1952). Psychology research in judgment and decision-making has shown that individuals often tend to simplify the world to cope with its complexity. Thereby, one of the strongest tendencies of humans is to classify objects into categories based on some similarity among them (Rosch & Lloyd, 1978). Already in the 1950s, Allport (1954) concludes that

framework which builds on this finding is mental accounting (Thaler, 1985, 1999; Shefrin & Statman, 1987). It describes the rules individuals engage in when grouping and evaluating outcomes and choices.

A common assumption of mental accounting theories applied to portfolio choice is that investors assign stocks to distinct mental accounts (i.e., stock-by-stock accounting, see Hartzmark, 2015; Frydman et al., 2017), whereby each mental account defines a separate investment episode (Barberis & Xiong, 2012). Outcomes within the same mental account are evaluated jointly, whereas outcomes across different mental accounts are evaluated separately. In particular, this framework implies that individuals are reluctant to integrate gains and losses across different mental accounts, which applied to a portfolio suggests that they do not evaluate outcomes across different stocks jointly, but rather distinctly as individual, stock-specific gains and losses.

However, once individuals evaluate a whole portfolio of stocks, information is often presented together, which suggests a joint rather than a separate evaluation. In situations in which information is presented together, research in psychology has shown that individuals focus on differences between the alternatives, when comparing information (Hsee, 1996; List, 2002; Kahneman, 2003). The most salient difference of stocks in a portfolio is probably whether a stock trades at a gain or at a loss, that is whether the purchase of the stock presents a good or a bad investment episode. In terms of categorical thinking, this suggests that stocks are assigned

evaluation of outcomes across mental accounts even across stocks which are all assigned to the same winner or loser category requires investors to integrate outcomes which they are reluctant to do and which takes cognitive effort, they may rather follow a simple counting heuristic when they evaluate portfolio investment decisions: They count the number of distinct mental accounts (i.e. stocks) they have assigned to one and the same category rather than aggregate outcomes across different mental accounts within and/or across different categories. As a consequence, investors compare the number of winner stocks to the number of loser stocks in the portfolio rather than the overall expected portfolio return to the overall portfolio risk.

loser stocks on the portfolio investment choice, we define a simple, counting-based measure of portfolio composition:

$$\frac{Number\ of\ winner\ stocks}{Number\ of\ winner\ stocks + Number\ of\ loser\ stocks}$$

A stock is counted as a winner stock, if the stock has a positive realized return since purchase and it is counted as a loser stock, if it has a negative realized return since purchase.[3]

B. Portfolio versus Individual Stock Level Information in the Field

Throughout this paper, we argue that portfolio investment decisions are impacted by information on how the entire portfolio performs as well as by information on how each individual position in the portfolio performs. However, this reasoning implies that investors receive or at least have access to this information (on the portfolio level as well as on the individual stock level) when they evaluate their self-selected or pre-determined (e.g., index funds) portfolios of stocks. An overview of how performance information is displayed by most online brokers and financial websites gives indication that investors have access to this information. Panel A in Figure 1 shows exemplary which performance information investors usually receive by their online broker when they log into their account. Performance information is provided on the overall portfolio level (e.g., the current portfolio value and the purchase value) as well as on the individual asset level (e.g., the return of each position in the portfolio). The information is similarly displayed if investors search online for the performance of pre-determined portfolios such as for example equity market indices. Panel B in Figure 1 shows exemplary which performance information an investor receives for the German equity market index DAX 30[4] on the publicly available financial website onvista. Again, the overall portfolio performance as well as the performance of each stock are clearly displayed.

In addition, the way performance information is displayed to investors suggests that they

In

particular, the color coding of gains and losses enhances the notion of categorical thinking since it facilitates the distinction between winner and loser stocks.

The media and some financial websites report counting-based composition measures similar to ours. The Wall Street Journal reports for US Stocks in its Markets Diary Section the

i.e., i.e., loser stocks),

For various equity market indices, the financial website onvista depicts the

[3] Later, in the fund flow analysis, we will define winner and loser stocks based on their daily returns.

[4] Since September 2021 the DAX index consists of 40 instead of 30 stocks. However, at the time of the analyses, the DAX only contained 30 stocks.

fraction

close to the overall index performance (see Figure 1).

2. Experimental Evidence

2.1 Experimental Design

In order to test whether the fraction of winners influences portfolio investment decisions, we design a setting with the following features: (1) portfolios with different fractions of winners, different portfolio returns, and different amounts of performance information can be exogenously assigned, (2) beliefs can be cleanly elicited and compared to a normative benchmark, and (3) learning about the underlying quality of stocks is possible and easy. To implement this, we conduct three experiments. All experiments are similarly designed with respect to design feature (1), but differ in the degree to which subjects can learn about the quality of assets (design features (2) and (3)).

A. Baseline Experimental Design

In this section, we outline the baseline experimental design, which is maintained for all three experiments. The experiments consist of two phases: a learning phase and an investment phase. In the learning phase, participants observe the performance of two portfolios, which both consist of ten different and equally-weighted stocks. The length of the learning period depends on the actual experiment (described below). In the subsequent investment phase, participants can allocate an endowment of $1,000 between both portfolios. To clearly identify a portfolio composition effect, we construct portfolios along two dimensions, which represent our main treatment variation. The first treatment dimension is the fraction of winner stocks in a portfolio. We focus on two different portfolio compositions which are mirrored images of one another.

W_S) consists of seven winner (i.e. positive realized return)

L_S)

consists of three winner and seven loser stocks. Importantly, the magnitude of the returns is determined such that the cross-sectional return variance is constant across portfolios.[5] The second treatment dimension is the overall portfolio return. A portfolio can either have a positive realized return of +10$ (G_P) or a negative realized return of 10$ (L_P).[6] We combine the two treatment dimensions to generate different *portfolios*. The following four *portfolios* result from

[5] We keep the cross-sectional variance of stock returns identical across portfolios to avoid a large heterogeneity in the size of returns across portfolios.

[6] In relative terms, the gain of $10 is equivalent to a positive return of 1% and the loss of $-10 is equivalent to a negative return of -1% given an initial investment of $1000 in each portfolio.

all possible combinations of our treatment dimensions: $G_p W_S$, $G_p L_S$, $L_p W_S$, and $L_p L_S$, where the first character denotes the overall portfolio return (marked by the index P for portfolio-level information) and the second character the portfolio composition (marked by the index S for stock-level information). Since we are interested in within-subject comparisons, i.e. portfolios, we combine two *portfolios* to one *portfolio pair*. An overview of all treatments is provided in Panel A of Table 1. Although we elicit every possible combination, our main focus will be on portfolio pairs $G_p W_S - G_p L_S$ and $L_p W_S - L_p L_S$. In these treatments, the overall portfolio returns are constant, but the fraction of winners differs. We will define these portfolio pairs as our baseline treatments, since they allow us to isolate the effect of different fractions of winner stocks in a portfolio on investment decisions.

Figure 2 demonstrates how *portfolio pairs* are presented to participants. Exemplary, the portfolio pair $G_p W_S - G_p L_S$ is shown. Both portfolios have the same realized positive return. However, portfolio $G_p W_S$ has a larger fraction of winner stocks than portfolio $G_p L_S$. The amount of information is deliberately reduced to a minimum to ensure a simple design which focuses on the main research question. At the same time, we ensure to provide the set of information investors usually obtain on the overview page of an online broker account. There are two levels of information. First, investors receive information on the individual stock level. They can see a list of their stock holdings and for each position the return in US dollar over the investment horizon. Second, they receive information on the overall portfolio level. They can observe the total return of their portfolio which is the sum of the dollar returns of the individual positions. The way we present return information by color coding gains and losses in green and red, respectively, is motivated by how investors usually observe returns in their online broker accounts and on financial websites (see Figure 1).[7]

Besides the fraction of winners and the overall realized portfolio returns, we also investigate whether providing portfolio-level performance information to subjects affects investment choice. In particular, we add a third treatment dimension that is whether overall portfolio returns are explicitly displayed or not. Taken together, this results in four baseline treatments ($G_p W_S - G_p L_S$ with portfolio returns displayed, $G_p W_S - G_p L_S$ without portfolio returns displayed, $L_p W_S - L_p L_S$ with portfolio returns displayed, and $L_p W_S - L_p L_S$ without portfolio returns displayed). We run all of these treatments in experiment one and two. In

[7] Besides the return information, participants are told about the number of shares held of each stock, the investment horizon and other relevant information in the introduction to the experiment. More details on the instructions can be found in Appendix A.

experiment three, we only run the treatment $G_pW_S - G_pL_S$ with portfolio returns displayed, but conduct two different conditions with respect to whether the portfolio variance is explicitly displayed.

to estimate the expected portfolio return and to assess the riskiness of both portfolios.[8] In Experiment 1, we additionally ask participants about their perceived satisfaction with both portfolios. At the end of the investment period, all returns are realized and paid out according to a conversion rate.[9]

B. The Return Generating Process

In this section, we describe the data-generating process that determines the underlying returns of our treatments. In other words, we describe how design features (2) and (3) are implemented. The return-generating process follows prior work by Grether (1980). In particular, there are two that draw returns from a bad distribution. Both distributions are binary and have symmetric stock-specific outcomes ($-X_i$ or X_i). In the good distribution, the probability that stock *i* increases in value by X_i is 70%, while the probability that it decreases in value by X_i is 30%. In the bad distribution, the probabilities are reversed, i.e. stock *i* increases in value by X_i with probability of 30%, while it decreases in value by X_i with probability of 70%. The expected return can easily be calculated and is $0.4X_i$ for a good stock and $0.4X_i$ for a bad stock. We chose X_i in such a way, that realized portfolio returns (in the baseline treatments) as well as the portfolio return volatility (i.e. the variance of portfolio returns) is identical for both portfolios. This ensures that the portfolios in our baseline treatments share identical expected risk-return characteristics measured by an identical Sharpe ratio. As a consequence of this design feature, we can demonstrate how an expected utility maximizing agent with mean-variance preferences should invest given the data generating process and the chosen portfolio options in our experiments. Based on standard portfolio theory (Markowitz, 1952), an agent achieves the largest overall Sharpe ratio by investing equal amounts in each of the two portfolios in our baseline treatments.[10]

Importantly, the degree to which subjects are informed (and can learn) about the data generating process differs across experiments. Panel B of Table 1 provides an overview of the

[8] Screenshots of the Experiments are provided in Appendix B.
[9] The endowment in experiment 3 is $10,000 instead of $1000 in experiment 1 and 2. This has a technical reason since otherwise it cannot be ensured with dollar changes in stock prices that at maximum the invested amount can be lost.
[10] More details are provided in Appendix C.

design features in which the experiments differ. In experiment one, we deliberately do not tell participants the underlying data generating process of stock returns. Participants observe a single return realization per stock (i.e., the length of the learning period is one), and can then, based on this information, form beliefs about expected returns. This experiment focuses on identical *realized* *expected* returns (since the data-generating process is unknown). In experiment two we communicate the underlying data-generating process, but keep the learning period the same as in experiment one. This ensures that not only realized but also expected returns are identical across portfolios, while still allowing direct comparisons to experiment one. To make sure that participants understand that both portfolios have identical realized and expected returns, we test their understanding in a number of comprehension questions while still eliciting their return expectations.

Finally, in experiment three we not only communicate the data-generating process but also increase the number of return realizations that participants observe (i.e., the learning phase) to 30. From observing these return realizations, participants can distribution and thus its expected return. From this information and the fact that stocks are equally weighted, they can calculate the expected return of the portfolio.[11] The computer helps subjects in doing the calculations. We want to emphasize that while subjects do not need to do the calculations themselves, we explain to them and also test their understanding of how the computer calculates expected returns by the answers they give to comprehension questions at the beginning of the experiment.[12] This extension of the design ensures that participants not only read about the expected return, but also experience the data-generating process and can actively learn from it. Prior studies have shown that such experience sampling can help to increase the general understanding of risk and leads to more consistent investment decisions (e.g., Kaufmann et al., 2013; Bradbury et al., 2015). Since we provide participants in experiment three with more return realizations than in experiment one and two, we have to adjust the way information is presented to participants. Figure 3 shows how information is displayed to participants in experiment three. Participants can see the number of positive return realizations, the number of negative return realizations, and the resulting total change in value of each stock. Summing up these individual dollar changes in value leads to the total change in portfolio value, which is clearly displayed below all portfolio holdings. We explain to participants that returns are presented as absolute changes in value and that portfolios are rebalanced at the end of the

[11] At first, participants do not know whether a stock draws returns from the good or bad distribution, i.e. it is equally likely that a stock draws returns from either of the two distributions. Since this information specifies the initial prior of participants, it is clearly stated in the instructions of the experiment.
[12] Instructions and comprehension questions can be read in Appendix A.

learning period to ensure equal weights of stocks when participants make the investment decision.

C. Experimental Procedure and Participants

1318 participants were recruited from a large crowdsourcing platform called Amazon Mechanical Turk (MTurk) to participate in three online experiments. MTurk advanced to a widely used and accepted recruiting platform for economic experiments. Not only does it offer a larger and more diverse subject pool as compared to lab studies (which frequently rely on students), but it also provides a response quality similar to that of other subject pools (Buhrmester et al., 2011; Goodman et al., 2013). The sample size, main hypotheses, and analyses are all pre-registered.[13] Table 2 presents summary statistics. 39% (34%, 30%) of the participants in experiment one (two, three) were female and the mean age of all participants was 34.7 years (33.9 years, 32.9 years). Participants report a medium level of stock-trading experience across all experiments.

2.2 Experimental Results

A. The Portfolio Composition Effect

We start by investigating

investment behavior. By utilizing the design of our first experiment, we can focus on instances in which two portfolios have identical realized portfolio returns but differ in the fraction of winner stocks (baseline treatments). Results are displayed Figure 4. The blue bars show average investment associated with portfolios that have a large fraction of winners (70% winners/30% losers), while the red bars show average investment in portfolios with a large fraction of losers (30% winners/70% losers). Results are split by the domain of the portfolio return (G: same positive return, L: same negative return) and whether the portfolio return is displayed or not.

Across all treatments, the blue bars are greater than the red bars, indicating a larger willingness to invest in portfolios with a larger fraction of winner stocks. For those portfolios which have the same realized positive return ($G_pW_S - G_pL_S$), participants invest on average \$265 out of \$1000 (p<0.001, two-sided t-test) more in the portfolio with more winners. For those portfolios which have the same realized negative return ($L_pW_S - L_pL_S$), participants invest on average \$187 out of \$1000 (p<0.001, two-sided t-test) more in the portfolio with more winners. One concern might be that the larger investment in portfolios with more winner stocks

[13] Pre-registration was done on Aspredicted.org. See https://aspredicted.org/blind.php?x=F74_BMJ and https://aspredicted.org/blind.php?x=M3B_RSL for the documents.

is since participants might wrongly infer that such portfolios have higher realized returns. To test this, we investigate the treatment in which overall portfolio returns are clearly displayed. In similar magnitude and significance, we once again find a pronounced portfolio composition effect. As such, we can confidentially rule out that the effect depends on whether the portfolio return is displayed.

Besides the investment, we also elicit

the portfolios, their beliefs about expected portfolio returns and risk. We find that all these

Irrespective of whether the portfolio return is displayed or not, we find that satisfaction levels are higher for those portfolios which consist of more winners. Additionally, we find that participants tend to provide more optimistic return expectations and lower risk assessments for those portfolios which have a larger fraction of winners. In particular, our findings suggest that the way participants form portfolio beliefs is affected by the fraction of winner stocks. While the performance on the portfolio level is identical, participants tend to be more optimistic about the portfolio which consists of a larger fraction of winners. Moreover, our results suggest an interesting driver of risk perception for portfolios: a larger fraction of loser stocks is related to more risk. So far, risk perception has mainly been analyzed for individual assets. Recent work by Holzmeister et al. (2020) and Zeisberger (2020) shows that risk perception is primarily driven by the probability of loss. Our findings are consistent with the idea that the number of loser stocks in a portfolio might be used by investors as an indicator for the probability of loss of a portfolio.

Taken together,

composition of winner and loser stocks on portfolio choice. Participants show a greater willingness to invest in portfolios with a larger fraction of winners, albeit portfolios achieved the same overall return. In line with the investment decision, participants report more optimistic return expectations and lower risk assessments for portfolios which consist of more winners.

B. Beliefs about Expected Returns

when two portfolios with different fractions of winners achieved the same *realized* return. Prior research has shown that investors strongly react to past returns. Such return-chasing behavior has been documented both at the individual investor level (e.g. Shefrin and Statman, 1985; Barber and Odean, 2008), as well as on a fund level (e.g. Sirri and Tufano, 1998; Barber, Huang, and Odean, 2016; or Berk and van Binsbergen, 2016). However, normative theory suggests that investors should base their investment decisions not on *realized past* returns, but instead on *expected* return and risk characteristics of a given portfolio. In this section, we aim to test whether a portfolio composition effect still exists when we keep not only *realized* returns, but also *expected* returns identical across portfolios. Such an analysis requires that individuals are informed about the full data-generating process behind portfolios (defined at the individual stock level). At the same time, it allows us to rule out that participants base their investment decision on expectations which they wrongly infer from realized past returns. We utilize the design of our second experiment in which the data generating process is clearly communicated and displayed to test for a portfolio composition effect when both *realized* and *expected* returns are identical.

Figure 5 displays the results. We start by comparing the average investments in each

In Panel A of Figure 5 we can replicate the findings from experiment one: Irrespective of whether the portfolio returns are displayed or not, we find that participants invest significantly more in the portfolio which consists of more winner stocks. For the treatment in which both portfolios have the same realized and expected positive return, participants invest on average \$339 (\$436 if portfolio returns are not displayed) more in the portfolio with more winners (both comparisons $p<0.001$; two-sided t-test). For the treatment in which both portfolios have the same realized and expected negative return, participants invest on average \$240 (\$322 if portfolio returns are not displayed) more in the portfolio with more winners (both comparisons $p<0.001$; two-sided t-test).

investment behavior still appears to be influenced by the fraction of winners of a portfolio. However, these average patterns may mask a substantial amount of heterogeneity driven by

expected portfolio returns. To test whether the effect still

beliefs about expected portfolio returns are identical, we rerun the analysis on the subsample of subjects who report as Bayes the same expected returns for both portfolios. Panel B of Figure 5 reports the results.[14] Even though participants in this subsample stated identical (and rational) beliefs about the expected portfolio return, we still find a sizable and statistically highly significant portfolio composition effect. For portfolios with positive realized return, participants invest on average \$356 more in the portfolio with a higher fraction of winners ($p<0.001$, two-sided t-test). Similarly, for portfolios with negative realized return, participants invest on average \$254 more in the portfolio with a higher fraction of winners ($p<0.001$, two-sided t-test). As before, we also elicit risk assessments. Participants rate those portfolios which consist of more loser stocks to be riskier than those

[14] We do not split the results by whether participants see the portfolio return due to too few observations.

portfolios which consist of more winner stocks. This result is consistent with their investment decision and replicates findings from experiment one.

C. Learning about Expected Returns

In experiment three, we put the effect of portfolio composition on investment choice to a severe test. We (i) extend the learning phase such that participants can observe a larger number of return realizations before they make their investment decision, (ii) provide computational support for the calculation of expected returns, and (iii) explicitly display to one group of participants not only the calculated expected return, but also the *portfolio return volatility*. This

about expected portfolio returns and their beliefs about volatility are identical across portfolios.

Figure 6 reports the average investment in each portfolio pooled and split by whether the portfolio volatility is displayed. U beliefs about expected returns, we find a strong effect. Participants invest on average \$2994 (out of \$10,000) more in the portfolio which consists of more winner than loser stocks (p<0.001). This finding is independent of whether the portfolio variance is displayed or not. In Panel B, we again focus our attention on participants who report subjective expected returns which match the objective

unbiased expectations but also that they have identical expectations for both portfolios.[15] However, even this group of participants invests on average \$4295 (out of \$10,000) more in the portfolio with more winners (p<0.001). Again, this finding is unaffected by whether the identical portfolio variance is displayed to subjects or not. In other words, the portfolio composition effect persists in situations in which expected portfolio returns and volatility cannot be the driving force of the observed differences in investments. Given the data generating process and the investment options, participants make suboptimal allocation decisions as the same overall expected return could be achieved with a smaller overall variance (Markowitz, 1952).

Similar to previous experiments, we also ask participants about a risk assessment for the portfolios. Figure 6 displays the average risk assessments beliefs about expected portfolio returns and volatility and for those subjects who report identical beliefs about expected portfolio returns and volatility. Consistent with results from previous experiments, we find that participants evaluate the portfolio with a larger fraction of winner

[15] As described in Section 1, the computer helps participants to calculate the expected portfolio returns from their evaluation of good and bad stocks. Based on this input, the computer also calculates the portfolio return volatility.

stocks to be less risky (p<0.001). If we restrict the sample to those subjects who report identical beliefs about expected returns and volatility, we still find that subjects evaluate the portfolio with more winners to be less risky than the portfolio with more losers (p<0.001).

D. Decomposing Portfolio Composition and Risk-Return Preferences

So far, we focused on our baseline treatments in which portfolios differ with respect to the fraction of winner and loser stocks but display identical risk and return characteristics. In this chapter, we now incorporate all possible treatments we ran in experiment one and two (see Table 1) into our analyses. Since we elicit all possible combinations of different portfolio compositions and portfolio returns, we have rich data to separately identify the effect of portfolio composition from the effect of portfolio returns
decision.

Table 3 displays differences in investment for portfolio pairs with identical return but different composition, different return but identical composition, and in which both, return and portfolio composition differ. Unsurprisingly, we find that the greatest difference of \$566 in investment manifests in portfolio pairs in which one portfolio trades at a gain and consists of more winner stocks relative to another portfolio which trades at a loss and consists of more loser stocks (p<0.001). Conversely, the smallest difference of \$206 manifests in instances in which return information is inconsistent with information regarding the portfolio composition (p<0.001). It is noteworthy that this difference shrinks to \$122 when portfolio returns are not explicitly displayed and is no longer significant at even the 10%-level. As such, it appears that if portfolio returns are not explicitly displayed to investors, they falsely infer portfolio performance from the fraction of winner stocks. Yet, if they know the overall portfolio return, they invest a greater amount in portfolios with higher return. This pattern already gives a first impression of the relationship between portfolio performance and portfolio composition. If return data is easily available and displayed, performance information is relatively more important than the fraction of winner and loser stocks. However, once portfolio information is not available, they approximate performance by counting the number of winner and loser stocks in the portfolio. Additionally, notice that this comparison provides further evidence for a portfolio composition effect. By comparing differences between the portfolio pairs $G_pW_S - L_pL_S$ and $G_pL_S - L_pW_S$, we keep the difference in overall realized (and expected) portfolio returns constant but flip the fraction of winners. This results in one portfolio pair with consistent information (i.e. a positive portfolio return goes along with a high fraction of winner stocks) and one portfolio pair with inconsistent information (i.e. a positive portfolio return goes along with a high fraction of loser stocks). If the fraction of winners does not matter for investment decisions, we expect to observe no significant difference of the differences in investment between the portfolio pairs ($Investment_{G_pW_S} - Investment_{L_pL_S} = Investment_{G_pL_S} - Investment_{L_pW_S}$). However, we find significant differences of \$359 (p<0.001) in investment which cannot be driven by differences in return.

To conclude this section, we run the following ordinary least squared regression models to test for a portfolio composition effect across all treatments of experiment one and experiment two.[16]

$$Investment_{ij} = \beta_0 + \beta_1 Gain_j + \beta_2 Winner_j + \beta_3 Gain_j \ x \ Winner_j + \varepsilon_{ij} \qquad (1)$$

$$\begin{aligned} Investment_{ij} = \beta_0 &+ \beta_1 Gain_j + \beta_2 Winner_j + \beta_3 Gain_j \ x \ Winner_j + \beta_4 Display_j \\ &+ \beta_5 Display_j \ x \ Gain_j + \beta_6 Display_j \ x \ Winner_j \qquad (2) \\ &+ \ \beta_7 \ Display_j \ x \ Gain_j \ x \ Winner_j + \varepsilon_{ij} \end{aligned}$$

The dependent variable $Investment_{ij}$ is the invested amount of subject *i* in portfolio *j*, $Gain_j$ is a dummy variable which is one if portfolio *j* made a gain, $Winner_j$ is a dummy variable which is one if portfolio *j* has a larger fraction of winner than loser stocks and $Display_j$ is a dummy variable which is one if the overall portfolio return is displayed. We use robust standard errors and cluster on the subject and the portfolio pair level. Table 4 reports the results for each experiment individually. Confirming our prior conjecture, we find that the strongest predictor of the investment decision is whether a portfolio is trading at a gain or not. However, we also find a pronounced and statistically highly significant portfolio composition effect. Subjects invest on average \$116.50 (\$147.30) more in the portfolio with a larger fraction of winner stocks. The effect is slightly stronger if the portfolio return is not displayed, albeit not statistically different.[17]

[16] We exclude experiment three from the regression analysis since we do not have variation in parameters other than the fraction of winners in the treatments we run in this experiment.

[17] -elicited level of satisfaction with the performance of the portfolios, their beliefs about expected returns and risk assessment are in line with the observed investment decisions (see Appendix D).

2.3 Alternative Explanations: Narrow and Broad Framing

The previous sections demonstrate that individuals make portfolio investment decisions as if they evaluate the attractiveness of a portfolio based on a simple counting heuristic of the composition of winner and loser stocks. This implies that investors tend to engage in a joint evaluation of individual stock outcomes which is complemented by taking portfolio-level information into account. In this section, we explore whether the portfolio composition effect is predicted by theories that assume either narrow-framing (stock-by-stock accounting) or broad framing (accounting based on the overall portfolio value) in isolation.

We first simulate how an agent who engages either in narrow or broad framing would behave in our experimental environment and then compare these predictions with the actual behavior of our participants. To do so, assume that an agent has cumulative prospect theory (CPT) preferences which are defined at the level of an individual asset (in case of narrow framing) or at the portfolio level (in case of broad framing):

$$\sum_{i=1}^{n} \pi_i v(x_i),$$

where

$$\pi_i = \begin{cases} w(p_i + \cdots + p_n) - w(p_{i+1} + \cdots + p_n) & for\ 0 \leq i \leq n, \\ w(p_{-m} + \cdots + p_i) - w(p_{-m} + \cdots + p_{i-1}) & for - m \leq i \leq 0 \end{cases}$$

and where $v(.)$ and $w(.)$ are known as the value function and the probability weighting function, respectively. In line with the suggestion of Tversky and Kahneman (1992), we assume the functional forms

$$v(x) = \begin{cases} x^{\propto} & for\ x \geq 0 \\ -\lambda(-x)^{\alpha} & for\ x < 0 \end{cases} \qquad \text{and} \qquad w(p) = \frac{P^{\delta}}{\left(P^{\delta} + (1-P)^{\delta}\right)^{1/\delta}}$$

where $\alpha, \delta \in (0,1)$ and $\lambda > 1$. Further, assume that an agent can invest in two portfolios, which are labeled *GW* and *GL*, as introduced in the experimental design. Both portfolios have identical positive expected return and identical standard deviation (both in the cross-section and in the time-series) but differ in the portfolio composition. In particular, whereas portfolio *GW* features a composition of seven winner stocks (i.e. positive realized return) and three loser stocks (i.e. negative realized returns), portfolio *GL* is exactly the opposite. Each of the 20 individual stocks that constitute the two portfolios have their own unique data-generating process, as depicted in Table C-1 in the Appendix. At each point in time *t*, individuals can choose to either invest in portfolio *GW* or *GL*, which determines their return for period *t+1*, at which point they can reallocate their investment. To obtain estimates for a wide variety of preference-parameter constellations, we follow Barberis (2012) and restrict our attention to preference parameter triples $(\alpha, \delta, \lambda)$ for which $\alpha \in [0,1]$, $\delta \in [0.3,1]$, and $\lambda \in [1,4]$. We next discretize each of the three intervals into a set of 20 equally spaced points and examine parameter triples where each parameter takes a value equivalent to one of the discrete points. In total, we thus study $20^3 = 8{,}000$ unique parameter triples.

A. Narrow Framing

We start by investigating the case of narrow framing, in which an agent evaluates each asset that constitutes a portfolio individually and subsequently aggregates these individual scores to an overall utility. Panel A of Figure 8 illustrates the simulation results. The red dots indicate parameter triples for which a CPT agent prefers the *GL* (Gain-Loser) portfolio, whereas the green dots indicate parameter triples for which she prefers the *GW* (Gain-Winner) portfolio.

Overall, the portfolio that consists of more winner than loser stocks (*GW*) is preferred in 4,913 out of 8,000 parameter triples, or in about 61 % of the possible combinations.

preference parameters $(\alpha, \delta, \lambda) = (0.88, 0.65, 2.25)$ would not prefer the winner-portfolio, but the loser-portfolio. Panel A of Figure 8 shows that a CPT agent is more likely to prefer the loser portfolio for high values of α, low values of δ, and low values of λ. The intuition is straightforward. The loser portfolio consists of a greater fraction of stocks which trade at a minor loss and a few stocks which trade at a large gain. As α increases, the marginal utility of additional gains diminishes less rapidly, which causes the agent to be more excited about the possibility to cushion the small losses with a large win. As δ falls, the agent overweights the tails of the probability distribution more heavily, which increases the desirability of the few stocks that might offer a large gain. Finally, as λ decreases, the agent becomes less loss averse. Thus, she is less scared by the large fraction of loser stocks and more willing to pick such a portfolio. Overall, these results demonstrate that an explanation for the portfolio composition effect which is solely based on narrow framing strongly depends on the assumed parameterization. In fact, the median agent in our experiment would even be assumed to act in an opposite way, rather preferring the *GL* portfolio over the *GW* portfolio. As such, we conclude that narrow framing alone can most likely not account for the documented behavior.

B. Broad Framing

Next, we turn to the case of broad framing, in which an agent only evaluates the overall portfolio outcome each period. Since the data-generating process is defined on the individual stock level, it is necessary to first estimate the distribution of portfolio returns from the distributions of the individual stock returns. To do so, we first run 10,000 independent simulations to obtain an estimate of the distribution of portfolio-level outcomes for each of the two portfolios.[18] Consistent with the stock-level information, the simulated distributions of both portfolios have an almost identical mean return of 4.05 and 4.07, with a standard deviation of 23.8 and 24.2 for the winner and loser portfolio, respectively, suggesting that the simulation was successful.[19] The main difference between both distributions is that the winner portfolio features a slightly broader distribution in terms of possible outcomes, which can lead to more extreme return realizations (both for gains and losses).

Next, we evaluate preferences regarding each portfolio for a CPT agent who frames outcomes broadly. Panel B of Figure 8 presents the simulation results. As before, the red dots indicate parameter triples for which a CPT agent prefers the *GL* (Gain-Loser) portfolio, whereas the green dots indicate parameter triples for which she prefers the *GW* (Gain-Winner) portfolio. In contrast to the narrow framing results, the portfolio that consists of more winner than loser stocks (*GW*) is preferred in only 2,434 out of 8,000 parameter triples, or in about 30 % of the

(1992) median

estimates of the preference parameters $(\alpha, \delta, \lambda) = (0.88, 0.65, 2.25)$ would prefer the loser-portfolio. Results in Panel B of Figure 8 indicate that portfolio *GL* becomes more attractive for a broad-framing CPT agent for higher values of δ, while both α and λ play a comparably minor and more nuanced role. The intuition for this relationship is as follows: Since both portfolios are constructed to have identical mean and standard deviation, the aggregate outcomes *at the portfolio-level* are on average relatively similar. As such, the higher fraction of loser stocks of the *GL* λ). Yet, since the *GL* portfolio has slightly less probability mass in the loss domain (due to the different kurtosis), it becomes relatively more attractive with higher values of λ. A similar argument can be made for α, since agents who broadly frame outcomes do not separately integrate stock-level information. Finally, as δ falls, the agent increasingly overweights the tails of the probability distribution, which directly interacts with the higher skewness of the *GW* portfolio and the

[18] Results for the simulated distribution are displayed in Figure D-VI in the Appendix.

[19] This also leads to both portfolios having an equal Sharpe Ratio of approximately 0.17, assuming a risk-free rate of 0%.

chance of obtaining a high gain. However, this relation only holds for low or moderate values of λ. For higher levels of loss aversion, the potential losses of the *GW* portfolio loom larger than the gains, such that an agent once again favors the *GL* portfolio.

Again, these results are not consistent with the documented portfolio composition effect. If anything, results for broad framing even suggest a reverse composition effect with more preference triples preferring the *GL*-portfolio over the *GW*-portfolio (inclu

3. From the Experiment to Financial Market Data

In a series of experiments, we have provided evidence that participants make portfolio investment decisions as if they evaluate portfolios based on a simple counting heuristic of their composition of winner and loser stocks. Next, we take this finding outside the lab and test whether portfolio composition also plays a role in financial markets. More precisely, we investigate whether the demand for leading equity market index funds is influenced by the fraction of winner stocks in the index.

Leading equity market indices of national economies represent ideal portfolio settings for our analysis. First, leading equity market indices are relatively stable and transparent predetermined portfolios with respect to the members over time. There are clear rules when a stock leaves or enters a national equity market index and these changes are communicated. Second, leading equity market indices capture a lot of attention in the media since they

Moreover, various publicly available financial websites as well as television news channels report not only the overall performance of equity market indices, but also the performance of their individual members.[20]

As measure for investor demand, we use fund flows of exchange-traded funds replicating the respective equity market index. Building on our experimental findings, we test whether a higher fraction of winner stocks in an index leads to larger subsequent fund flows.

A large body of papers in the literature analyzes the relation between fund flows and fund returns. Several studies find return chasing behavior of actively-managed mutual fund investors indicated by the positive relation between future flows of mutual funds and their

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[20] For example, the WSJ reports for US Stocks in its Markets Diary Section the number of stocks that were

such
Also, TV news channels such as n-tv or CNN show on banners on the bottom of the screen the performance of individual members of market indices.

returns (Ippolito, 1992; Gruber, 1996; Warther, 1995; Sirri & Tufano, 1998; Edelen & Warner, 2001; Coval & Stafford, 2007; Ben-Rephael, Kandel, & Wohl, 2011). Besides actively-managed mutual funds, return-chasing behavior has even been observed for index mutual funds (Elton, Gruber, & Busse, 2004; Kim, 2011). For ETFs, the return-flow relation has received much less attention in the literature so far and from those studies which exist, there is less clear-cut evidence of whether ETF flows are influenced by returns. Clifford, Fulkerson, and Jordan (2014) use monthly data to test drivers of ETF flows and find return-chasing behavior by investors, while Kalaycioglu (2004) does not find return-chasing behavior for ETFs with daily data.

A. Data

We test our hypothesis using daily fund flow data of leading equity market index ETFs for the period January 2010 to December 2019. Our sample focuses on four leading equity market indices. An overview of the equity market indices in our sample is provided in Table 5.

Based on the data availability, our sample comprises selected European as well as US equity market indices. For each national economy in our sample, we chose the leading equity market index of the respective country (e.g. the CAC 40 for France, the DAX 30 for Germany, etc.) and then search for ETFs replicating the index. Importantly, ETFs only enter the sample if their investment objective is to replicate the index as closely as possible. We exclude all index ETFs which use hedging strategies or claim in their investment objective that they use other strategies to systematically deviate from the index (e.g. minimum variance, excluding financial industry). We verify the investment objective of all index ETFs in our sample by hand on the

We obtain fund-level data from Morningstar. For each ETF (identified by its SecId and FundId), we download daily net asset value (NAV), return, number of shares outstanding and total net assets (TNA). Fund flows, our main variable of interest, are measured as daily dollar flows divided by TNA at the end of the prior day. Dollar flows are calculated following Morningstar and as is common in the literature as difference between two consecutive

n.[21] For the calculation of our main independent variable, the fraction of winner stocks in an index, we download stock return data from Thomson Reuters Datastream. Each day, we define each stock as either a winner stock (positive daily return) or a loser stock (negative daily return). Stocks with zero daily return do

[21] Fund flow on day t = (Shares on day t * NAV on day t) (Shares on day t-1 * NAV on day t-1) * (1+ return on day t), see estimated net cash flow methodology by Morningstar

not enter the composition measure on that day. Indices change their members from time to time. To account for these changes, we hand collect data from Bloomberg on the days on which an index in our sample experiences a change in its members and identify which stock leaves and which enters the index. Based on the stock return data and the index member changes, we calculate the fraction of winner stocks of an index as defined in Section 1.

Before we turn to the main analysis, we provide summary statistics for our measure of portfolio composition. Table 6 Panel A reports the descriptive statistics of the daily fraction of winner stocks in an index. The mean and median fraction of winners a day is close to 0.5, that is 50% of the index members have realized a positive return and 50% have realized a negative return. The percentiles of the portfolio compositions show that there is wide variation in the fraction of winner stocks of an index per day; the 10th percentile is 9.7% and the 90th percentile is 90%.

Table 6 Panel B summarizes how our measure of portfolio composition is related to index returns. In particular, it shows the distribution of the fraction of winner stocks by index return intervals. As expected, there is a positive relation between the index return on a given day and the fraction of winner stocks in the index. A larger fraction of winner stocks is related to a larger index return. However, and crucial for this study, there is a considerable variability in portfolio compositions for a given, fixed index return interval. That means an index return can be achieved by different portfolio compositions. For example, a daily index return of 1% can be achieved by less than 50% winner stocks, but also by more than 90% winner stocks.[22]

B. Main Result

Our unique dataset, which is set up of fund-level as well as stock-level data, allows us to test our hypothesis. We run the following regression model (similar to Clifford, Fulkerson, & Jordan, 2014 and Staer, 2017):

$$Flow_{i,j,t} = \alpha + \sum_{l=0}^{m} \beta_{R,l}\, Fund\_Return_{i,j,t-l} + \sum_{l=0}^{m} \beta_{C,l}\, Composition_{i,j,t-l} + \varepsilon_{i,j,t}$$

In the panel regression, the dependent variable $Flow_{i,j,t}$ represents the fund flow of ETF i on index j on day t, $Fund\_Return_{i,j,t-l}$ represents the return of ETF i on index j on day $t-l$, where l represents the number of lags, and $Composition_{i,j,t-l}$ represents the fraction of

[22] A graphical presentation of the relation between the fraction of winners and the index return is provided in Figure D-VI in the Appendix.

winner stocks of ETF i on index j on day $t-l$, where l represents the number of lags.[23] The panel model includes fund and day fixed effects. We double cluster residuals by index and day to account for correlation across indices. The results are summarized in Table 7.

In our sample of leading equity market indices, we find a positive relation between the index composition of winner stocks and subsequent fund flows. In particular, we find that an equity market index ETF are affected by one to two days lagged composition of winner and loser stocks of the index. Across all leading equity market indices in our sample, we estimate that a composition of 100% winner stocks leads to roughly 0.025% greater inflows in two days than a composition of 50% winner and 50% loser stocks. Given that the average TNA of a fund in our sample is 1.8 billion dollars, that would imply a greater inflow of roughly 0.5 million dollars for a fund with a 100% winner fraction relative to a 50% winner fraction. On a yearly basis, these point estimates indicate that funds with a 10% larger fraction of winner stocks experience 1.25% greater inflows per year, which implies 23 million dollars for the average index fund in our sample. The effect remains statistically significant and decreases only slightly in magnitude when controlling for the index return (column 2). The results change only marginally if we include the fraction of winner stocks and the index return of the day of the observed fund flow to the regression model (columns 3 and 4). Solomon, Soltes, and Sosyura (2014) find that funds with high past returns attract extra flows, but only if these stocks were recently featured in the media. Additionally, they demonstrate that the effect on flows is driven more by rewarding funds that hold media-covered winners than penalizing funds that hold media-covered losers. Our results show that winner stocks attract fund flows not only because they receive disproportionate media coverage but also because investors use them as a proxy for predicting future returns. Moreover, we find a tendency of return-chasing behavior for ETF investors which is in line with Clifford, Fulkerson, and Jordan (2014) and with several studies on mutual fund flow data (Ippolito, 1992; Gruber, 1996; Warther, 1995; Sirri & Tufano, 1998; Edelen & Warner, 2001).

C. Robustness Analyses

We run several robustness analyses in this section. Can the effect be observed in weekly data? Does the effect depend on extreme portfolio compositions? How is the effect related to comparable measures such as the skewness of the daily returns of index members?

[23] In what follows we discuss the results of the main regression model with three days lagged. In the Appendix we provide results of the regression model with five days lagged. The results are similar.

First, we replicate the main finding using weekly instead of daily data. We calculate the weekly portfolio composition as the arithmetic mean of all daily portfolio compositions over one week. Table 8 reports the results. We find two main results. First, the index composition of week *t* is positively related to the fund flows of week *t*. In numbers, a weekly index composition of 75% winner and 25% loser stocks leads to roughly 0.25% greater inflows in this week than an index composition of 50% winner and 50% loser stocks. The effect changes marginally in statistical significance and size when controlling for the index return. Second, the previous index . This result is consistent with the observation that the lagged fraction of winner stocks becomes pretty quickly insignificant using daily data as shown in Table 7. The short-living character of the effect is in line with the idea that people may rather remember and act upon the observation that the majority of index achieved a positive daily return yesterday and potentially also two days ago, but may neither remember nor act anymore upon the same observation one week ago.

Second, we examine whether the effect is driven by extreme index compositions. Extreme index compositions represent days on which all members of an index have realized positive returns or days on which all members of an index have realized negative returns. These extreme index compositions may be caused by specific events such as the passing of a trade agreement, changes in the base rate of central banks or the spread of a disease which are likely to affect all members of an index in a similar direction. After unexpected bad news, it is likely that all members of an index trade at a daily loss, whereas after unexpected good news it is likely that all members of an index trade at a daily gain. To test whether these days primarily drive the effect, we include to our regression model ll-winner- all members of an index trade at a gain -loser- members of an index trade at a loss. We also add these dummies lagged by one, two, and three days. The results are reported in Table 9. We find that none of the all-winner/all-loser-dummies gains statistical significance. Even after controlling for days with extreme index compositions, the coefficients of the one-day and two-day lagged fraction of winners remain statistically significant and change only slightly in economic magnitude compared to the results in Table 7.

Finally, we examine whether the fraction of winner stocks proxies for skewness. We measure skewness as the third moment of the daily stock returns of an index. Skewness is related intuitively to our portfolio composition measure as follows: For a given positive index return that is composed of many (small/medium) winner stocks and few (large) loser stocks the resulting return distribution over the index members tends to be negatively skewed. For the same index return, the reversed composition, i.e. few (very large) winner stocks and many (small) loser stocks tend to result in a positively skewed distribution. While the fraction of winner stocks is related to skewness, there are distinct differences between the two measures. Skewness takes the size of the individual returns of the index members into account, whereas our measure of portfolio composition does not. However, from skewness per se portfolio compositions cannot be inferred. The reason is that skewness does not tell anything about the location of the return distribution. As such a positively skewed distribution can be located entirely in the negative domain, partly in the negative and positive domain, or entirely in the positive domain. This parallel shift of the distribution keeps the third moment unaffected, but results in substantially different fractions of winners of an index. We test whether the portfolio composition effect persists once we control for the skewness of the stock returns of the index members. The results are reported in Table 10. We find that the portfolio composition effect persists after controlling for the skewness of the returns of the index members. In particular, the two-day lagged portfolio composition coefficient remains statistically significant and changes only marginally in size. Although most of the skewness variables do not gain statistical significance, their coefficients enter the model negatively. This is consistent with the intuition presented above that for a given positive index return negative skewness tends to be related to large fractions of winner stocks which are related to greater fund inflows.

4. Discussion and Conclusion

In this study, we analyze how investors evaluate portfolios. Motivated by two well-known frameworks from psychology, which are category-based thinking and mental accounting, we test whether a simple counting-based measure of performance the fraction of winner stocks in a portfolio affects the willingness to invest in a portfolio. Across all experiments, we find that individuals invest more in portfolios with a larger fraction of winner stocks than in alternative portfolios with a larger fraction of loser stocks, albeit the portfolios have realized identical overall returns. The documented effect persists, if we keep the expected returns and volatility identical across portfolios. Deviating from theories that assume volatility to be the common measure of risk, we find that participants associate portfolios with a larger fraction of loser stocks with more risk.

We use our well-identified experimental evidence on individ

portfolio investment decisions to test whether the fraction of winner stocks also matters in financial markets. Consistent with our experimental evidence, we find that subsequent fund flows of leading equity market index funds are affected by the index fraction of winner stocks.

Overall, our results support the importance of the portfolio for investor behavior. While much evidence demonstrates that investors do not form optimal portfolios, the portfolio plays a key role for investor behavior in various facets: be it that a portfolio resembles a limited consideration set (Hartzmark, 2015), that a portfolio provides aggregate performance information (An et al., 2019), or as we demonstrate that overall performance is differently evaluated given the performance of its components. An interesting direction for future studies might be to identify further dimensions of a portfolio that matter to investors and to examine how the different dimensions of a portfolio affect investor behavior.

Studies have shown that mental accounting is a powerful framework to explain many aspects of investor behavior. A common assumption in these models is that investors assign stocks in their portfolio to distinct mental accounts (i.e. stock-by-stock accounting see Frydman et al, 2017). However, how investors form, track, and evaluate mental accounts over time and across assets is still not parsimoniously understood. This is important since assumptions on the dynamics of mental accounting are crucial to the predictions of these models. Our findings shed light on how mental accounts are evaluated in a portfolio and as such across stocks. Several studies find that investors behave as if they engage in narrow framing of stocks in their portfolios. Our results suggest that investors compare mental accounts across stocks when they evaluate their portfolios. That is, they frame outcomes narrowly on the individual stock level, but engage in a joint evaluation of these narrowly framed outcomes to evaluate portfolios. How narrow framing and joint evaluation of stocks in a portfolio interact across different investors and over time is one question worth of further study.

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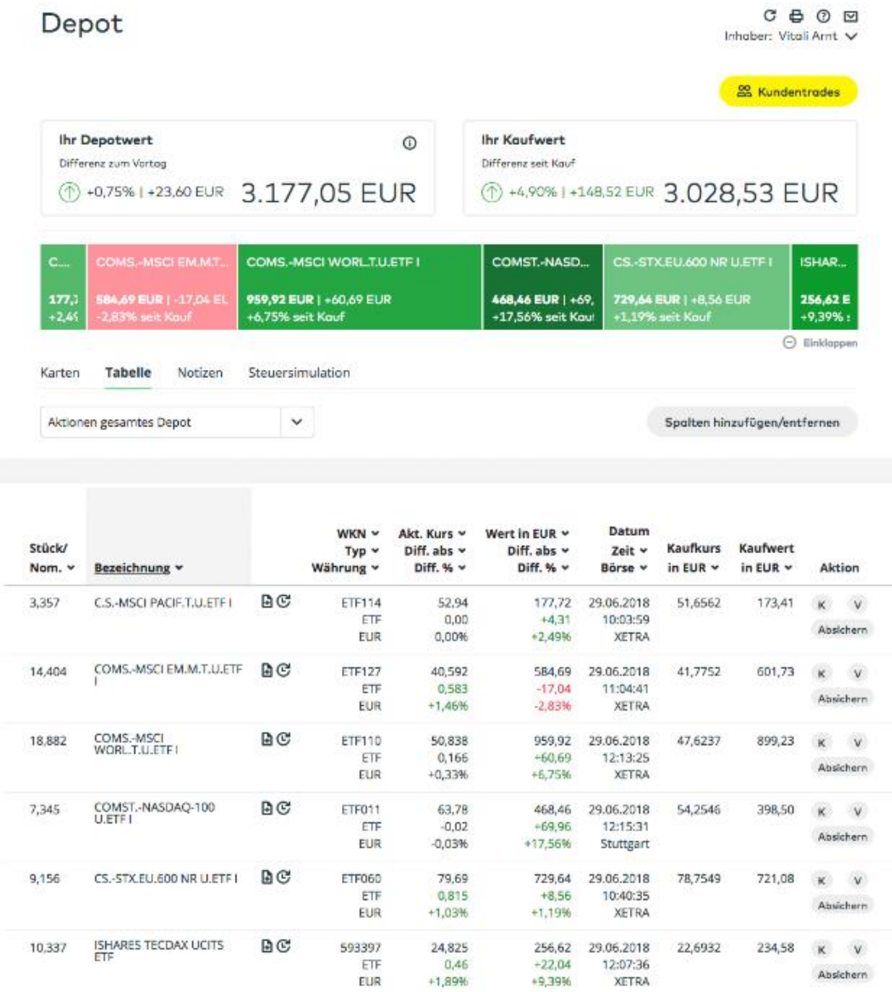
Figure 1: How Portfolio Performance Information Is Displayed

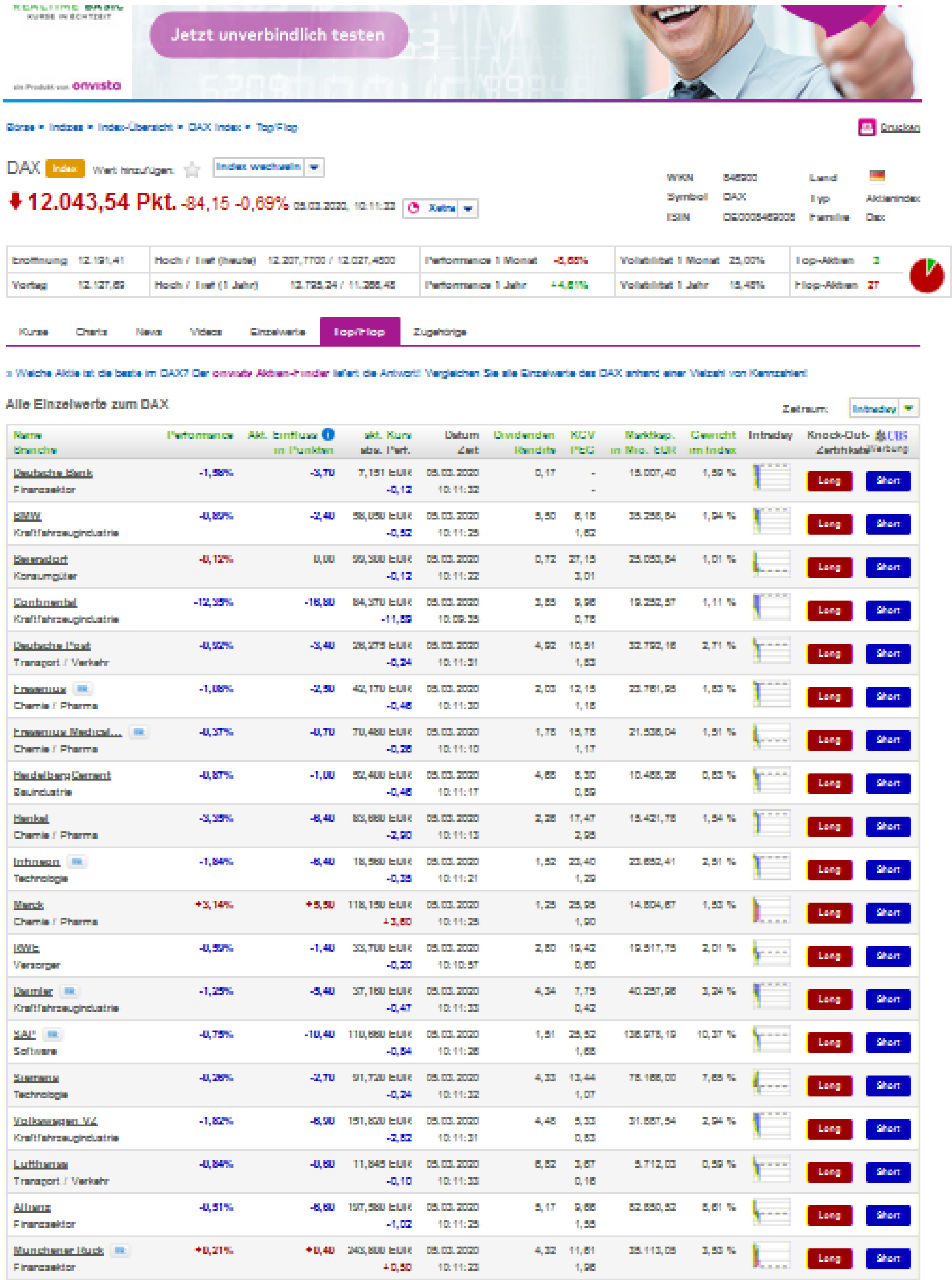
Panel A of this figure shows a screenshot of how performance information of a portfolio is usually displayed to investors by online brokers and Panel B shows how performance information of leading equity market indices (e.g. the German market index DAX 30) is presented to investors on financial websites.

Panel A: Performance Information Displayed by an Online Broker (Comdirect)



Stück/ Nom.	Bezeichnung	WKN Typ Währung	Akt. Kurs Diff. abs Diff. %	Wert in EUR Diff. abs Diff. %	Datum Zeit Börse	Kaufkurs in EUR	Kaufwert in EUR	Aktion
3,357	C.S.-MSCI PACIF.T.U.ETF I	ETF114 ETF EUR	52,94 0,00 0,00%	177,72 +4,31 +2,49%	29.06.2018 10:03:59 XETRA	51,6562	173,41	K V Absichern
14,404	COMS.-MSCI EM.M.T.U.ETF I	ETF127 ETF EUR	40,592 0,583 +1,46%	584,69 -17,04 -2,83%	29.06.2018 11:04:41 XETRA	41,7752	601,73	K V Absichern
18,882	COMS.-MSCI WORL.T.U.ETF I	ETF110 ETF EUR	50,838 0,166 +0,33%	959,92 +60,69 +6,75%	29.06.2018 12:13:25 XETRA	47,6237	899,23	K V Absichern
7,345	COMST.-NASDAQ-100 U.ETF I	ETF011 ETF EUR	63,78 -0,02 -0,03%	468,46 +69,96 +17,56%	29.06.2018 12:15:31 Stuttgart	54,2546	398,50	K V Absichern
9,156	CS.-STX.EU.600 NR U.ETF I	ETF060 ETF EUR	79,69 0,815 +1,03%	729,64 +8,56 +1,19%	29.06.2018 10:40:35 XETRA	78,7549	721,08	K V Absichern
10,337	ISHARES TECDAX UCITS ETF	593397 ETF EUR	24,825 0,46 +1,89%	256,62 +22,04 +9,39%	29.06.2018 12:07:36 XETRA	22,6932	234,58	K V Absichern

Panel B: Performance Information on a Financial Website (onvista)



Name / Branche	Performance	Akt. Einfluss in Punkten	akt. Kurs / abs. Perf.	Datum / Zeit	Dividenden Rendite	KGV / PEG	Marktkap. in Mio. EUR	Gewicht im Index	Intraday	Knock-Out-Zertifikate
Deutsche Bank / Finanzsektor	-1,58%	-3,70	7,151 EUR / -0,12	05.03.2020 / 10:11:32	0,17	- / -	15.007,40	1,59 %		Long Short
BMW / Kraftfahrzeugindustrie	-0,89%	-2,40	58,050 EUR / -0,52	05.03.2020 / 10:11:25	5,50	6,18 / 1,62	35.258,54	1,94 %		Long Short
Beiersdorf / Konsumgüter	-0,12%	0,00	99,300 EUR / -0,12	05.03.2020 / 10:11:22	0,72	27,15 / 3,01	25.053,54	1,01 %		Long Short
Continental / Kraftfahrzeugindustrie	-12,35%	-16,80	84,370 EUR / -11,89	05.03.2020 / 10:09:35	3,85	9,98 / 0,78	19.252,57	1,11 %		Long Short
Deutsche Post / Transport / Verkehr	-0,92%	-3,40	26,275 EUR / -0,24	05.03.2020 / 10:11:31	4,92	10,51 / 1,53	32.792,16	2,71 %		Long Short
Fresenius / Chemie / Pharma	-1,08%	-2,50	42,170 EUR / -0,46	05.03.2020 / 10:11:30	2,03	12,15 / 1,18	23.761,95	1,53 %		Long Short
Fresenius Medical... / Chemie / Pharma	-0,37%	-0,70	70,480 EUR / -0,26	05.03.2020 / 10:11:10	1,75	15,75 / 1,17	21.536,04	1,51 %		Long Short
HeidelbergCement / Bauindustrie	-0,87%	-1,00	52,400 EUR / -0,46	05.03.2020 / 10:11:17	4,85	8,30 / 0,59	10.455,26	0,83 %		Long Short
Henkel / Chemie / Pharma	-3,35%	-6,40	83,660 EUR / -2,90	05.03.2020 / 10:11:13	2,26	17,47 / 2,95	15.421,75	1,54 %		Long Short
Infineon / Technologie	-1,84%	-6,40	18,560 EUR / -0,35	05.03.2020 / 10:11:21	1,52	23,40 / 1,29	23.652,41	2,51 %		Long Short
Merck / Chemie / Pharma	+3,14%	+5,50	118,150 EUR / +3,60	05.03.2020 / 10:11:25	1,25	25,95 / 1,90	14.504,67	1,53 %		Long Short
RWE / Versorger	-0,59%	-1,40	33,700 EUR / -0,20	05.03.2020 / 10:10:57	2,80	19,42 / 0,60	19.517,75	2,01 %		Long Short
Daimler / Kraftfahrzeugindustrie	-1,25%	-5,40	37,160 EUR / -0,47	05.03.2020 / 10:11:33	4,34	7,75 / 0,42	40.257,96	3,24 %		Long Short
SAP / Software	-0,75%	-10,40	110,660 EUR / -0,84	05.03.2020 / 10:11:26	1,51	25,52 / 1,66	138.975,19	10,37 %		Long Short
Siemens / Technologie	-0,26%	-2,70	91,720 EUR / -0,24	05.03.2020 / 10:11:32	4,33	13,44 / 1,07	78.166,00	7,65 %		Long Short
Volkswagen VZ / Kraftfahrzeugindustrie	-1,82%	-6,90	151,620 EUR / -2,82	05.03.2020 / 10:11:31	4,45	5,33 / 0,53	31.557,54	2,94 %		Long Short
Lufthansa / Transport / Verkehr	-0,84%	-0,60	11,845 EUR / -0,10	05.03.2020 / 10:11:33	6,82	3,67 / 0,16	5.712,03	0,59 %		Long Short
Allianz / Finanzsektor	-0,51%	-6,60	197,580 EUR / -1,02	05.03.2020 / 10:11:25	5,17	9,66 / 1,55	82.550,52	8,61 %		Long Short
Münchener Rück / Finanzsektor	+0,21%	+0,40	243,800 EUR / +0,50	05.03.2020 / 10:11:23	4,32	11,61 / 1,96	35.113,05	3,53 %		Long Short

Figure 2: Portfolio Pair $G_pW_S - G_pL_S$ as presented in Experiment 1 and 2

This figure presents the portfolio pair $G_pW_S - G_pL_S$. Portfolio X correspondents to the portfolio G_pW_S and Portfolio Y correspondents to the portfolio G_pL_S.

Portfolio X	
Stock A	4
Stock B	10
Stock C	-5
Stock D	-7
Stock E	2
Stock F	5
Stock G	2
Stock H	-9
Stock I	5
Stock J	3
Total	10

Portfolio Y	
Stock K	-2
Stock L	-4
Stock M	-2
Stock N	8
Stock O	-5
Stock P	5
Stock Q	-1
Stock R	-2
Stock S	14
Stock T	-1
Total	10

Figure 3: Portfolio Pair $G_pW_S - G_pL_S$ as presented in Experiment 3

This figure presents the portfolio pair $G_pW_S - G_pL_S$. Portfolio X correspondents to the portfolio G_pW_S and Portfolio Y correspondents to the portfolio G_pL_S. For each stock, the binary outcomes are displayed in parentheses, the number of positive return days, the number of negative return days and the total change in value are shown.

Portfolio X

Stock		Number of positive return days	Number of negative return days	Total change in value
Stock A	(+/-4)	**21**	**9**	**48**
Stock B	(+/-10)	**22**	**8**	**140**
Stock C	(+/-6)	**7**	**23**	**-96**
Stock D	(+/-7)	**8**	**22**	**-98**
Stock E	(+/-2)	**22**	**8**	**28**
Stock F	(+/-5)	**20**	**10**	**50**
Stock G	(+/-2)	**24**	**6**	**36**
Stock H	(+/-9)	**10**	**20**	**-90**
Stock I	(+/-6)	**21**	**9**	**72**
Stock J	(+/-3)	**22**	**7**	**42**
Total change in portfolio value				**132**

Portfolio Y

Stock		Number of positive return days	Number of negative return days	Total change in value
Stock K	(+/-2)	**3**	**27**	**-48**
Stock L	(+/-3)	**12**	**18**	**-18**
Stock M	(+/-2)	**11**	**19**	**-16**
Stock N	(+/-8)	**24**	**6**	**144**
Stock O	(+/-5)	**8**	**22**	**-70**
Stock P	(+/-6)	**21**	**9**	**72**
Stock Q	(+/-1)	**11**	**19**	**-8**
Stock R	(+/-2)	**11**	**19**	**-16**
Stock S	(+/-12)	**19**	**11**	**96**
Stock T	(+/-1)	**13**	**17**	**-4**
Total change in portfolio value				**132**

Figure 4: Baseline Treatments of Experiment 1

The figure for the two portfolio pairs $G_pW_S - G_pL_S$ and $L_pW_S - L_pL_S$,

perception for each portfolio elicited on a Likert scale from 1: low risk to 7: high risk. The blue bars refer to the portfolios with more winner stocks and the red bars refer to the portfolios with more loser stocks. Results are separately shown for treatments in which portfolio returns are not displayed and for treatments in which portfolio returns are displayed. Displayed are 95%-confidence intervals.

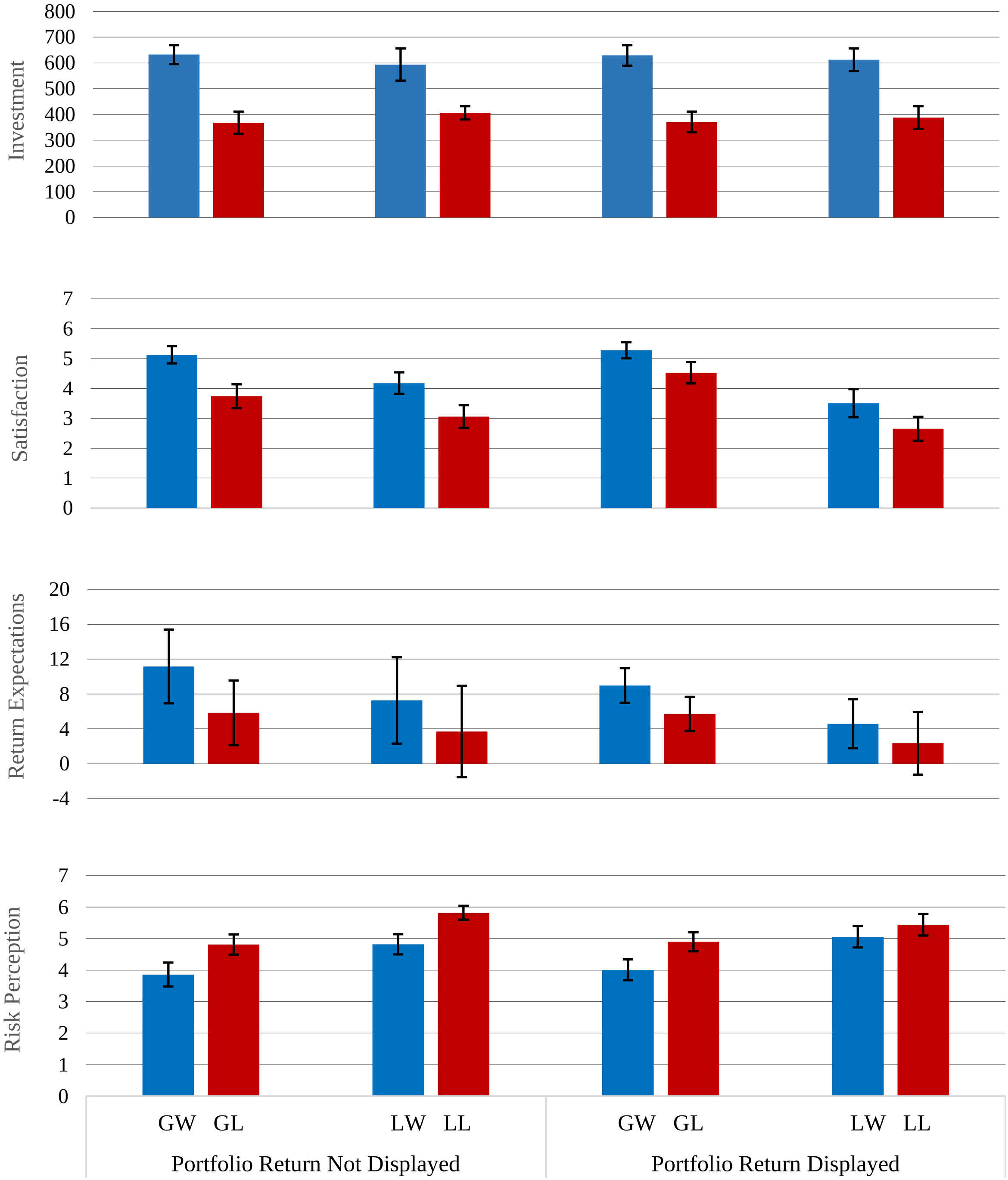
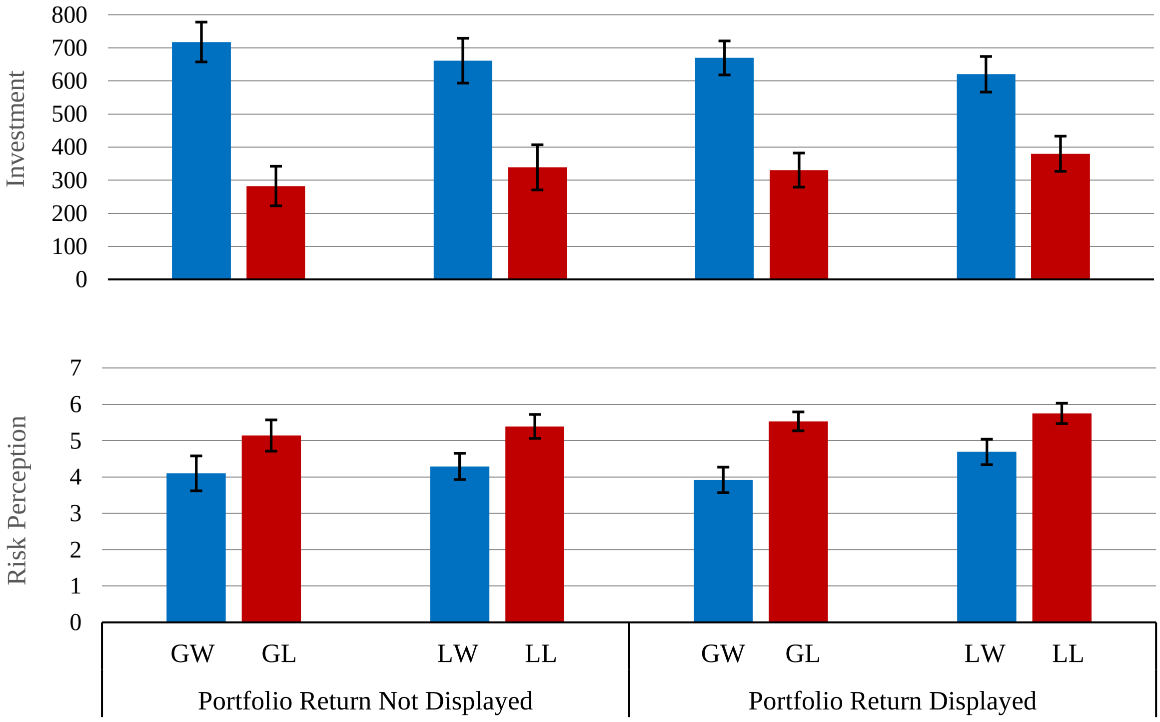


Figure 5: Baseline Treatments of Experiment 2

Panel A $G_pW_S -$
G_pL_S and $L_pW_S - L_pL_S$ and
low risk to 7: high risk.
participants who state the same expected returns for the two portfolios of a pair. The blue bars refer to the portfolios with more winner stocks and the red bars refer to the portfolios with more loser stocks. Results are separately shown for treatments in which portfolio returns are not displayed and for treatments in which portfolio returns are displayed. Displayed are 95%-confidence intervals.

Panel A: Investment and Risk Perception



Panel B: Investment Conditional on Return Expectations

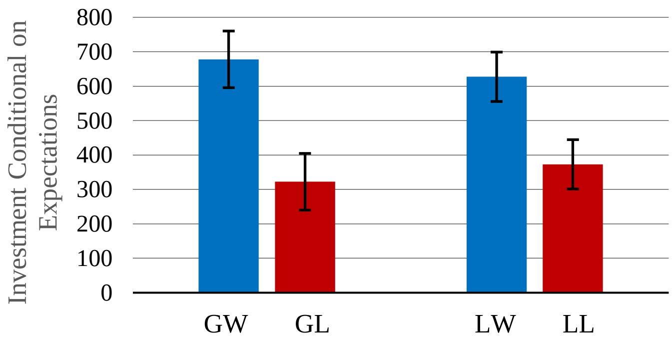


Figure 6: Baseline Treatment of Experiment 3

The figure $G_pW_S -$ G_pL_S and $L_pW_S - L_pL_S$, for those participants who state the same expected returns for the two portfolios, on a Likert scale from 1: low risk to 7: high risk, and participants who state the same expectations about returns and variance of returns. The blue bars refer to the portfolios with more winner stocks and the red bars refer to the portfolios with more loser stocks. Results are shown pooled and separated by treatment (portfolio variance not displayed and portfolio variance displayed). Displayed are 95%-confidence intervals.

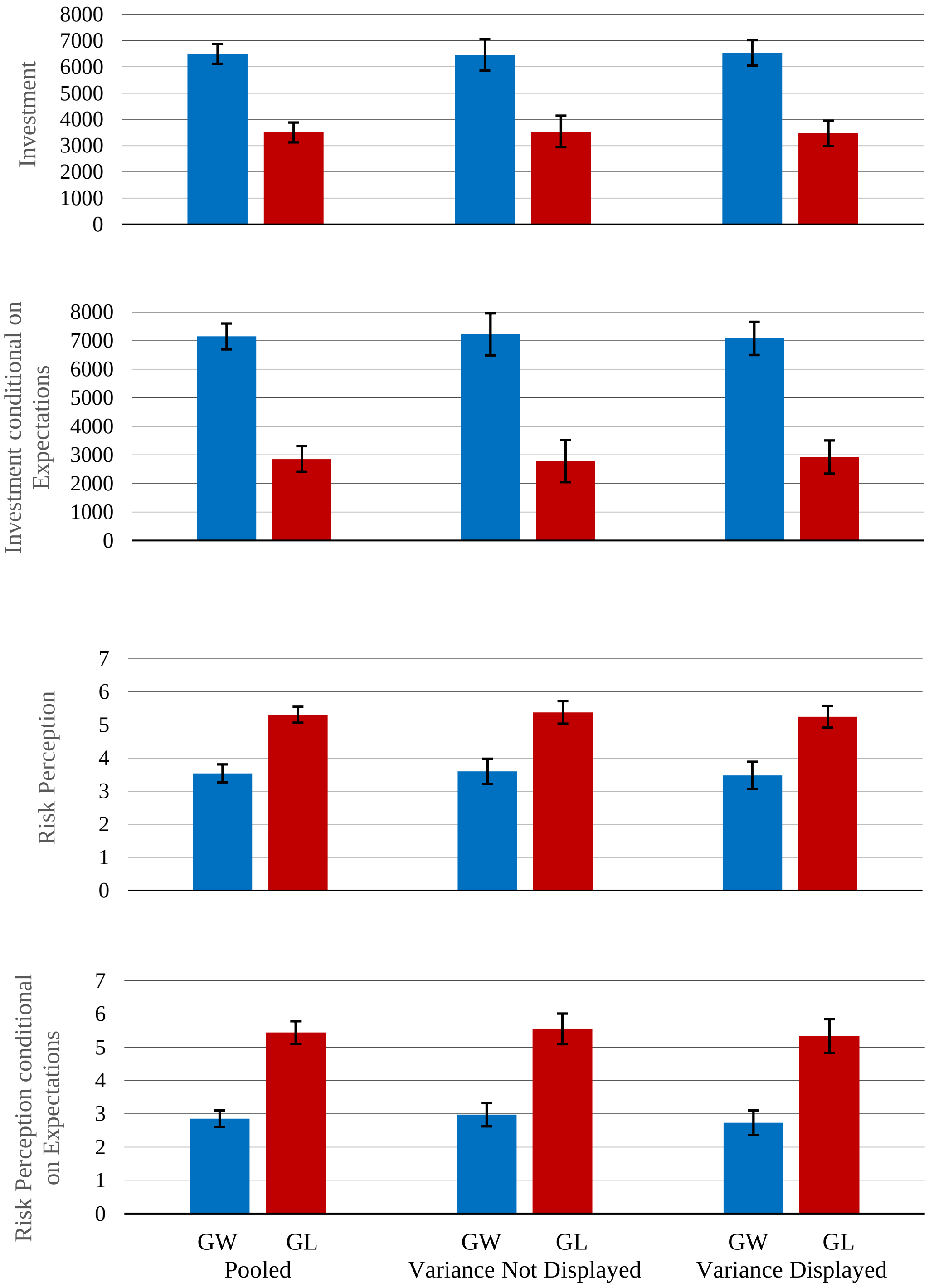
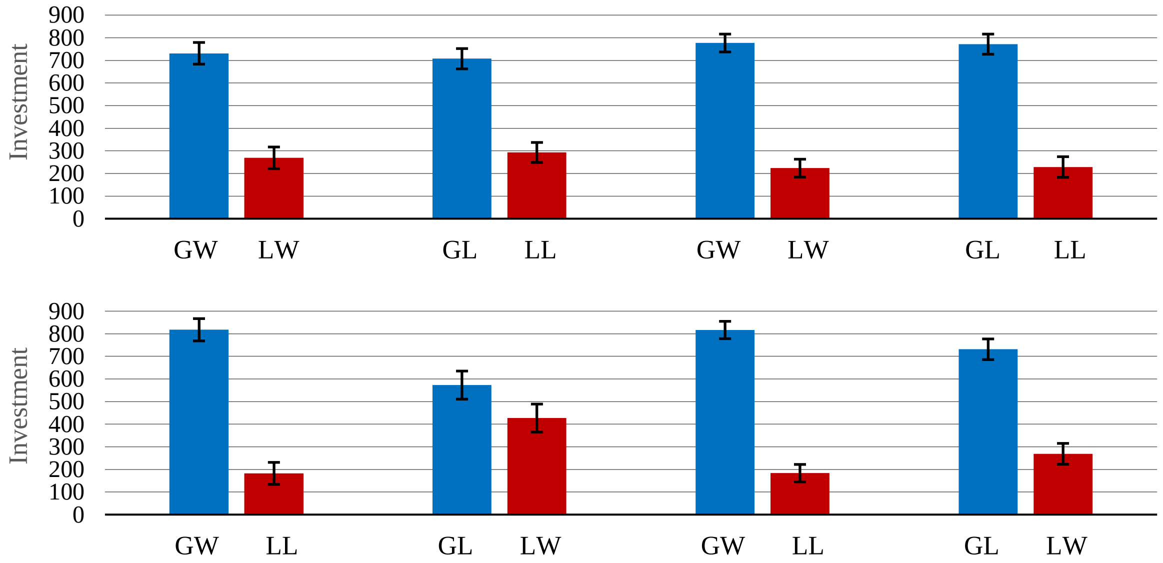


Figure 7: Additional Treatments of Experiment 1 and 2

$G_pW_S -$ L_pW_S, $G_pL_S - L_pL_S$, $G_pW_S - L_pL_S$ and $G_pL_S - L_pW_S$. Panel A reports the results for Experiment 1 and Panel B for Experiment 2. The blue bars refer to the portfolio with an overall positive return and the red bars refer to the portfolio with an overall negative return. Displayed are 95%-confidence intervals.

Panel A: Investment Experiment 1



Panel B: Investment Experiment 2

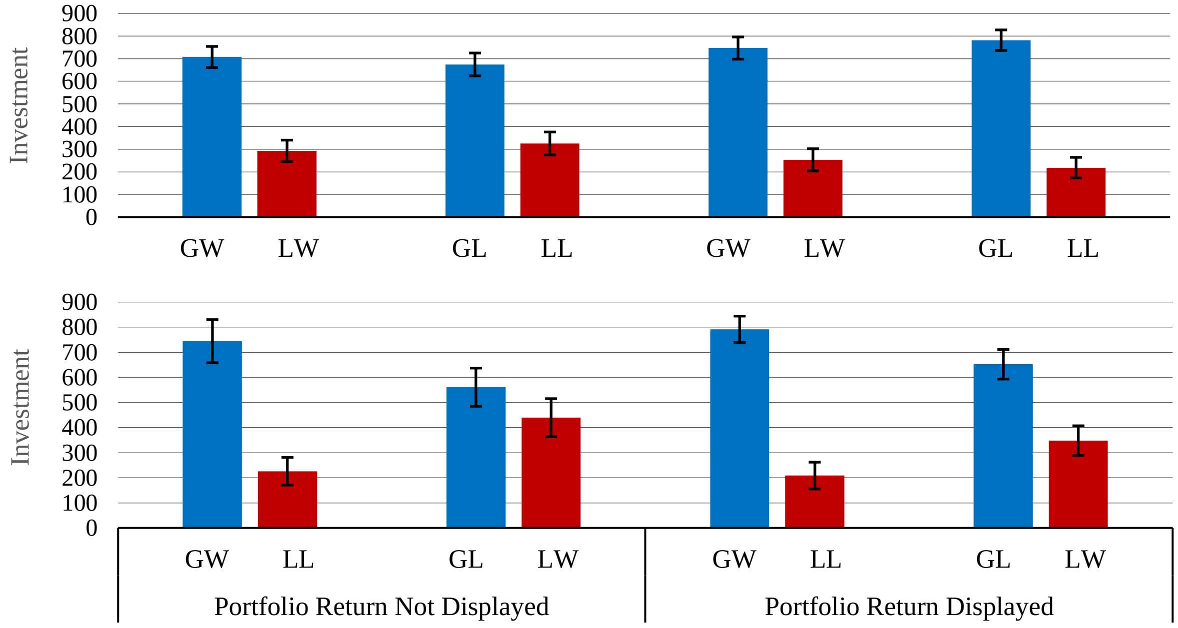
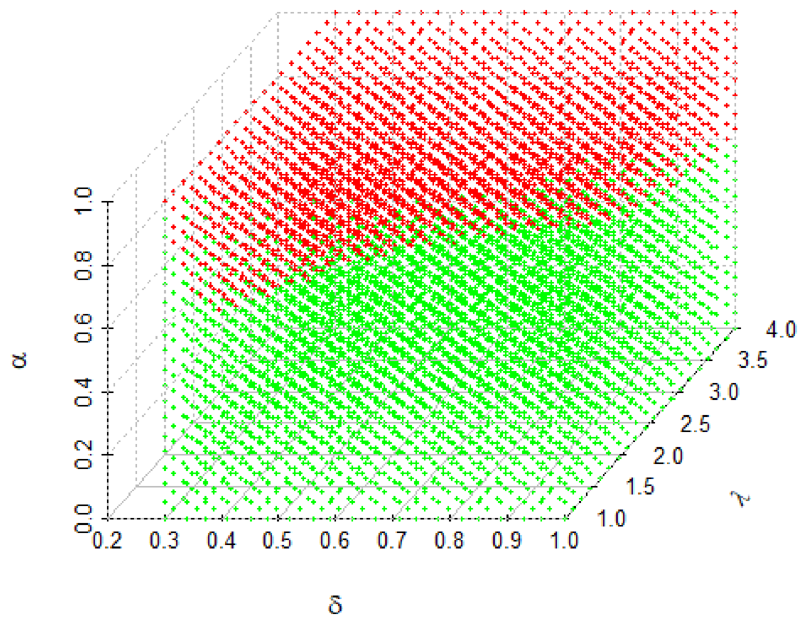


Figure 8: Prospect Theory Preference Parameter Triples for Narrow and Broad Framing

This figure displays preference parameter triples $(\alpha, \delta, \lambda)$ for which an agent with prospect theory preferences who frames outcomes narrowly (Panel A) or broadly (Panel B) would prefer a portfolio with more winner stocks (green dots) or with more loser stocks (red dots) holding expected return and standard deviation constant. A lower value of α means greater concavity (convexity) of the prospect theory value function over gains (losses); a lower δ means more overweighting of tail probabilities; and a higher λ means greater loss aversion.

Panel A: Portfolio Choices for Narrow Framing



Panel B: Portfolio Choices for Broad Framing

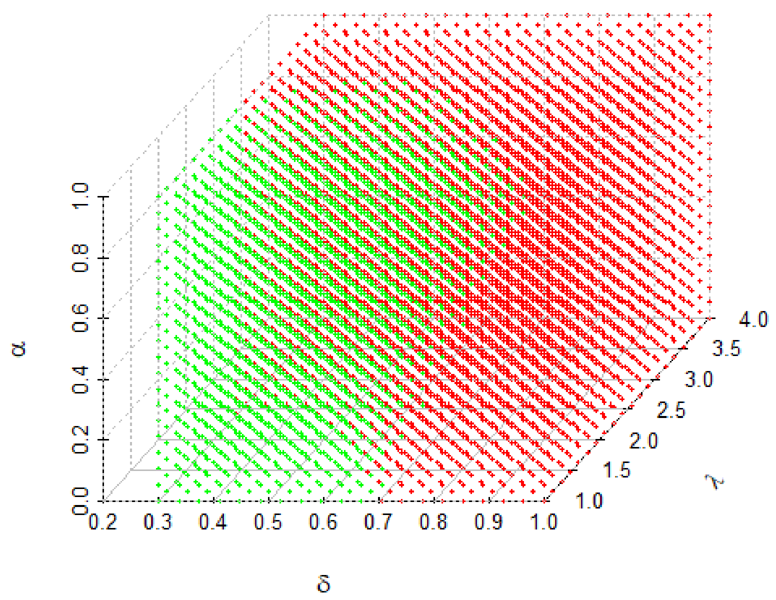


Table 1: Treatments and Design Differences Across Experiments

Our experiments have in total six treatments (except for experiment 3 with only one treatment). Each treatment has two portfolio pairs. A portfolio pair consists of two portfolios. Portfolios differ in one or several of three treatments dimensions which are (1) overall portfolio return, (2) fraction of winners and (3) the display of the portfolio return. Portfolio pairs are described by letter pairs (e.g. $G_pW_S - G_pL_S$). The first letter of each pair corresponds to the overall portfolio return (G_p: Portfolio trades at a gain, L_p: Portfolio trades at a loss) and the second letter corresponds to the fraction of winners (W_S: More winner than loser stocks, L_S: More loser than winner stocks). For example, the label $G_pW_S - G_pL_S$ means that both portfolios of this pair trade at the same gain denoted by the first letter G_p, but differ in the fraction of winners denoted by the second letter W_S and L_S. Panel A displays an overview of all treatments of our experiments. Panel B shows an overview of how the design features differ across experiments.

Panel A: Treatments

Treatment	Treatment dimensions			Portfolio pair 1	Portfolio pair 2
	Overall portfolio return	Fraction of winners	Total portfolio return displayed		
1	same	different	yes	$G_pW_S - G_pL_S$	$L_pW_S - L_pL_S$
2	same	different	no	$G_pW_S - G_pL_S$	$L_pW_S - L_pL_S$
3	different	same	yes	$G_pW_S - L_pW_S$	$G_pL_S - L_pL_S$
4	different	same	no	$G_pW_S - L_pW_S$	$G_pL_S - L_pL_S$
5	different	different	yes	$G_pW_S - L_pL_S$	$G_pL_S - L_pW_S$
6	different	different	no	$G_pW_S - L_pL_S$	$G_pL_S - L_pW_S$

Panel B: Design Differences Across Experiments

	Experiment 1	Experiment 2	Experiment 3
Treatments (see Panel A)	1-6	1-6	1
Portfolio pair	1 & 2	1 & 2	1
Data generating process	unknown	known	known
Number of periods	2	2	60
Expected return and variance displayed	No	No	Yes & No

Table 2: Summary Statistics on Subjects

This table shows summary statistics for our experimental data. Reported are the mean and the standard deviation (in parentheses) for the three experiments (Columns 1 to 3). *Female* is an indicator variable that equals 1 if a participant is female. *Statistical skills* -assed statistical skills on a 7-point Likert scale. The variable was only elicited for Experiment 2 and 3. *Experience in Stock Trading* is the self-reported experience participants have in stock trading, assessed by a 7-point Likert scale.

Variable	**Experiment 1 (N = 483)**	**Experiment 2 (N = 607)**	**Experiment 3 (N = 228)**
Age	34.72	33.86	32.87
	(10.96)	(10.33)	(9.06)
Female	0.39	0.34	0.30
	(0.49)	(0.48)	(0.46)
Statistical Skills (1-7)		4.23	4.58
		(1.60)	(1.41)
Experience in Stock Trading (1 - 7)	3.73	3.96	4.13
	(1.82)	(1.85)	(1.78)

Table 3: Investment Comparison for Different Portfolio Returns and Compositions

This table shows pairwise t-tests for investments in different portfolio pairs. Pairs differ in whether they have the same return but a different composition, a different return but the same composition, or whether they differ in both dimensions. We cluster standard errors on the individual investor level and on the portfolio pair level, standard errors are reported in parentheses, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Same Return Diff. Composition		Diff. Return Same Composition		Diff. Return Diff. Composition	
Portfolio 1	G_pW_S	L_pW_S	G_pW_S	G_pL_S	G_pW_S	G_pL_S
Portfolio 2	G_pL_S	L_pL_S	L_pW_S	L_pL_S	L_pL_S	L_pW_S
Investment 1	693.47	637.71	726.14	724.06	782.76	603.07
	(19.76)	(21.18)	(17.10)	(17.98)	(19.12)	(25.00)
Investment 2	306.53	362.29	273.86	275.94	217.24	396.93
	(19.76)	(21.18)	(17.10)	(17.98)	(19.12)	(25.00)
Difference	386.93***	275.42***	452.28***	448.11***	565.52***	206.13***
p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

Table 4: Regression Results of Investment

The table shows the coefficients of OLS regressions of investment on a gain dummy variable (1 if portfolio trades at a gain), a winner dummy variable (1 if portfolio has more winner than loser assets), the interaction term of gain and winner, a display dummy variable (1 if total portfolio return is displayed) and multiple interaction terms of the display, gain and winner dummy variable. Regression (1) and (2) are run with data from experiment 1, regression (3) and (4) are run with data from experiment 2. We cluster standard errors on the individual investor level and on the portfolio pair level, standard errors are reported in parentheses, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	*Investment*			
	Experiment 1		Experiment 2	
	(1)	(2)	(3)	(4)
Gain	311.2***	260.6***	264.9***	222.0***
	(17.61)	(24.99)	(21.52)	(30.61)
Winner	116.5***	131.9***	147.3***	151.5***
	(16.17)	(23.60)	(20.49)	(30.41)
Gain x Winner	28.08	41.73	36.17	62.12
	(21.82)	(31.72)	(27.57)	(39.43)
Display		-28.43		-22.72
		(19.82)		(23.36)
Display x Gain		101.2***		88.89**
		(35.00)		(42.70)
Display x Winner		-30.75		-8.746
		(32.20)		(40.94)
Display x Gain x Winner		-27.30		-54.89
		(43.58)		(54.90)
Constant	279.1***	293.3***	284.8***	296.4***
	(9.919)	(14.50)	(11.67)	(16.93)
Observations	1,936	1,936	1,213	1,213
R^2	0.346	0.353	0.323	0.327

Table 5: Sample of Market Indices

The table lists the four leading equity market indices investigated in our study with the respective number of stocks in the index.

Market Index	Country	Number of stocks
CAC 40	France	40
DAX 30	Germany	30
Dow Jones	US	30
Euro STOXX 50	Eurozone	50

Table 6: Sample Descriptive Statistics

Using data from Thomson Reuters Datastream and Bloomberg for the period from January 2010 to December 2019, we calculate the daily portfolio composition measure for each of the equity market indices of our sample. The portfolio composition is defined as the fraction of stocks of an index with positive realized daily return (winner stocks). Panel A reports the distribution of the daily distribution of the portfolio composition. Panel B shows how portfolio compositions are related to index returns. For various index return intervals of length 0.5%, the distributions of portfolio compositions are provided.

Panel A: Distribution of Portfolio Composition

		Percentiles					
Mean	SD	P10	P25	Median	P75	P90	Skew
0.508	0.290	0.097	0.267	0.517	0.750	0.900	-0.077

Panel B: Relation between Portfolio Composition and Index Return

			Percentiles				
Index Return	Mean	SD	P10	P25	Median	P75	P90
>0.02	0.940	0.084	0.833	0.920	0.960	1.000	1.000
(0.015, 0.020]	0.863	0.134	0.694	0.800	0.900	0.960	1.000
(0.010, 0.015]	0.817	0.147	0.612	0.750	0.860	0.922	0.967
(0.005, 0.010]	0.711	0.158	0.488	0.612	0.739	0.833	0.900
(0, 0.005]	0.583	0.168	0.354	0.479	0.600	0.700	0.800
(-0.005, 0]	0.418	0.177	0.194	0.290	0.417	0.537	0.646
(-0.010, -0.005]	0.290	0.162	0.098	0.167	0.268	0.388	0.500
(-0.015, -0.010]	0.182	0.158	0.032	0.061	0.140	0.265	0.380
(-0.020, -0.015]	0.114	0.118	0.000	0.024	0.080	0.167	0.260
<-0.020	0.068	0.117	0.000	0.000	0.033	0.082	0.163

Table 7: Portfolio Composition and Fund Flows – Daily Data

The table summarizes results of panel regressions of the dependent variable *Fund Flow* on day t on *Portfolio Composition* on day t and up to three days lagged and *Fund Return* on day t and up to three days lagged. We use fund and day fixed effects and double-cluster standard errors on the index and day level, t-statistics are reported in parentheses, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	*Fund Flow t*			
	(1)	(2)	(3)	(4)
Composition t			0.000290	0.000586*
			(1.85)	(2.51)
Composition t-1	0.000335*	0.000202	0.000364**	0.000242*
	(2.67)	(1.91)	(3.21)	(2.34)
Composition t-2	0.000545**	0.000490**	0.000565**	0.000501**
	(4.08)	(3.87)	(4.24)	(3.99)
Composition t-3	0.000300	0.000249	0.000312	0.000261
	(2.11)	(1.74)	(2.14)	(1.76)
Fund Return t				-0.0142*
				(-2.38)
Fund Return t-1		0.00575*		0.00330
		(2.79)		(1.87)
Fund Return t-2		0.00417*		0.00378*
		(3.10)		(2.74)
Fund Return t-3		0.000848		0.000651
		(0.59)		(0.47)
Constant	-0.000481**	-0.000360*	-0.000655**	-0.000683**
	(-3.41)	(-3.12)	(-5.80)	(-5.16)
Observations	92026	88057	91835	87874
R^2	0.041	0.039	0.040	0.039
Fund FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES

Table 8: Portfolio Composition and Fund Flows – Weekly Data

The table summarizes results of panel regressions of the dependent variable *Fund Flow* in week t on *Portfolio Composition* in week t and up to three weeks lagged and *Fund Return* in week t and up to three weeks lagged. We use fund and week fixed effects and double-cluster standard errors on the index and day level, t-statistics are reported in parentheses, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable		*Fund Flow t*		
	(1)	(2)	(3)	(4)
Composition t			0.0100**	0.0123*
			(3.25)	(2.53)
Composition t-1	0.00625	0.00568	0.00662	0.00592
	(1.11)	(0.87)	(1.20)	(0.93)
Composition t-2	0.00303	0.00428	0.00342	0.00421
	(0.67)	(1.02)	(0.78)	(0.98)
Composition t-3	0.00652	0.00831	0.00686	0.00834
	(1.41)	(1.71)	(1.48)	(1.65)
Fund Return t				-0.0446
				(-0.88)
Fund Return t-1		0.0106		0.00402
		(0.53)		(0.24)
Fund Return t-2		-0.0195		-0.0202
		(-1.01)		(-1.05)
Fund Return t-3		-0.0299		-0.0294
		(-1.98)		(-1.89)
Constant	-0.00710	-0.00833	-0.0128*	-0.0147*
	(-1.16)	(-1.33)	(-2.40)	(-2.97)
Observations	20166	20166	20166	20166
R^2	0.042	0.042	0.049	0.042
Fund FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES

Table 9: Extreme Portfolio Compositions and Fund Flows

The table summarizes results of panel regressions of the dependent variable *Fund Flow* on day t on *Portfolio Composition* on day t and up to three days lagged, *All Winner* dummy which is one if all stocks are winners on day t and the dummy lagged up to three days, *All Loser* dummy which is one if all stocks are losers on day t and the dummy lagged up to three days and *Fund Return* on day t and up to three days lagged. We use fund and day fixed effects and double-cluster standard errors on the index and day level, t-statistics are reported in parentheses, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	*Fund Flow t*			
	(1)	(2)	(3)	(4)
Composition t			0.000285	0.000572*
			(1.90)	(2.61)
Composition t-1	0.000366*	0.000232	0.000387**	0.000265*
	(2.88)	(2.08)	(3.33)	(2.36)
Composition t-2	0.000545**	0.000502**	0.000565**	0.000513**
	(4.14)	(3.96)	(4.34)	(4.12)
Composition t-3	0.000292	0.000248	0.000302	0.000257
	(2.17)	(1.78)	(2.18)	(1.79)
All Winners t			0.0000868	0.000122
			(0.49)	(0.61)
All Winners t-1	-0.0000966	-0.000170	-0.0000889	-0.000155
	(-0.78)	(-1.50)	(-0.73)	(-1.41)
All Winners t-2	-0.0000305	0.0000108	-0.0000275	0.0000149
	(-0.26)	(0.09)	(-0.23)	(0.12)
All Winners t-3	0.0000651	-6.54e-08	0.0000632	0.00000671
	(0.29)	(-0.00)	(0.29)	(0.03)
All Losers t			0.0000730	0.0000269
			(0.52)	(0.18)
All Losers t-1	0.000168	0.000190	0.000114	0.000131
	(0.66)	(0.87)	(0.42)	(0.55)
All Losers t-2	-0.0000243	0.000128	-0.0000252	0.000130
	(-0.17)	(0.88)	(-0.18)	(0.87)
All Losers t-3	-0.00000130	-0.0000165	-0.000000939	-0.0000123
	(-0.00)	(-0.05)	(-0.00)	(-0.03)
Fund Return t				-0.0142*
				(-2.35)
Fund Return t-1		0.00592*		0.00344
		(2.93)		(1.96)
Fund Return t-2		0.00425*		0.00385*
		(3.05)		(2.70)
Fund Return t-3		0.000850		0.000663
		(0.61)		(0.49)
Constant	-0.000495**	-0.000386**	-0.000664***	-0.000699**
	(-3.91)	(-3.53)	(-6.10)	(-4.79)
Observations	92026	88057	91835	87874
R^2	0.041	0.039	0.040	0.039
Fund FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES

Table 10: Skewness and Fund Flows

The table summarizes results of panel regressions of the dependent variable *Fund Flow* on day t on *Portfolio Composition* on day t and up to three days lagged, the *Skewness* of the stock returns of the index members on day t and up to three days lagged and *Fund Return* on day t and up to three days lagged. We use fund and day fixed effects and double-cluster standard errors on the index and day level, t-statistics are reported in parentheses, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	*Fund Flow t*	
	(1)	(2)
Composition t		0.000599*
		(2.53)
Composition t-1	0.000210	0.000250*
	(2.01)	(2.42)
Composition t-2	0.000502**	0.000516**
	(3.96)	(4.09)
Composition t-3	0.000260	0.000270
	(1.87)	(1.86)
Skewness t		-0.0000189
		(-0.67)
Skewness t-1	-0.00000747	-0.00000337
	(-0.40)	(-0.17)
Skewness t-2	-0.0000287	-0.0000310
	(-1.75)	(-1.79)
Skewness t-3	-0.0000363*	-0.0000346*
	(-2.61)	(-2.50)
Fund Return t		-0.0141
		(-2.32)
Fund Return t-1	0.00572*	0.00328
	(2.81)	(1.81)
Fund Return t-2	0.00420*	0.00382*
	(2.93)	(2.52)
Fund Return t-3	0.000852	0.000651
	(0.54)	(0.42)
Constant	-0.000375**	-0.000704**
	(-3.38)	(-5.03)
Observations	88057	87874
R^2	0.041	0.042
Fund FE	YES	YES
Time FE	YES	YES

Internet Appendix

Part A: Instructions

Experiment 1

Dear participant,

You participate in an experiment on decision making which is part of a research study at the University of Mannheim.

In the following you will be presented with the performance of two portfolios of stocks. Each portfolio consists of ten different stocks. Please imagine that you bought the respective stocks one month ago. You invested equal amounts of money in each stock. Now you observe the performance of the stocks in each of your portfolios.

Please take your time and ask yourself how you would feel when observing the performance. There are two pairs of portfolios. It is possible that the second pair of portfolios is shown to you before the first pair of portfolios.

Overall, this study will take 3-5 minutes. You will be compensated $0.50 for the successful completion of this HIT on MTurk.

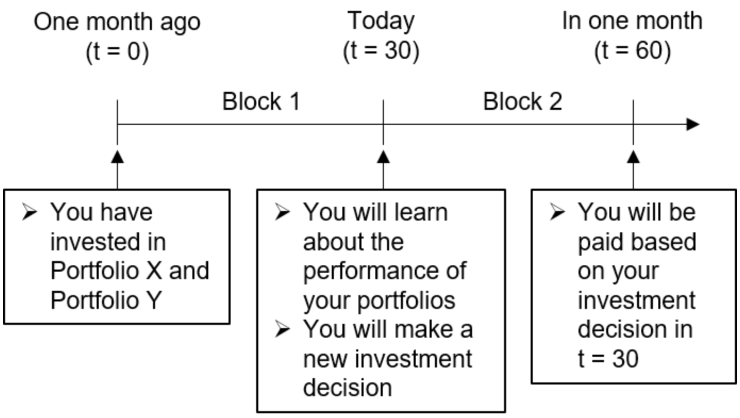
Experiment 3

Dear participant,

You participate in an experiment on decision making which is part of a research study at the University of Mannheim. Please read all instructions carefully. Your payment depends on your decisions. Overall this study will take approximately 10 minutes.

In the following you will be presented with the performance of two portfolios of stocks (**Portfolio X and Portfolio Y**). Each portfolio consists of ten different stocks. Please imagine that you have bought the respective stocks in period 0 (t = 0). To be precise, you have invested 10,000 ECU (experimental currency unit) in Portfolio X and 10,000 ECU in Portfolio Y in period 0. Within each portfolio, you have invested **equal amounts in each stock** (i.e. 1,000 ECU in each stock). More about the exchange rate between ECU and $ is described at the end of the instructions.

Today, you are in period 30 (see graph below) and you observe the performance of your portfolios. In particular, you will see how each stock in each of your portfolios has performed over 30 periods (block 1). Before you make any further decision, both portfolios will be rebalanced (the weight of each stock will be reset to 1/10). Then, at the beginning of block 2, you will be asked to make a **return forecast** for each portfolio and an **investment decision** for the next 30 periods. Importantly, while the weights of the stocks are reset between the blocks, the stocks themselves in your portfolios remain the same.



How do stock prices change over time?

Each period, the price of a stock can either increase by z or decrease by -z (z is supposed to be a variable that takes an absolute value). How likely it is that a stock price increases or decreases depends on its type. There are two types: A stock can be a **good stock** or a **bad stock**. If the stock is a good stock, the probability that the price increases is 70% and the probability that the price decreases is 30%. While, if the stock is a bad stock, the probability that the price increases is 30% and the probability that the price decreases is 70%.

In the beginning (t = 0), you do not know whether a stock is a good or a bad stock. As such, it is equally likely that a stock will be good or bad, i.e. the probability is exactly 50%. The table gives an overview of the types of stocks with the probability distributions.

	Good stock	**Bad stock**
Probability of **price increase by z**	0.70	0.30
Probability of **price decrease by -z**	0.30	0.70
Expected change in price	$0.40 \cdot z$	$-0.40 \cdot z$

Today, in period 30, you will observe 30 price changes for each stock. From this information, you can learn whether a stock is more likely to be a good or a bad stock. If you observe more increases in price than decreases, the stock is more likely to be a good stock, while if you observe more decrease in price than increases, the stock is more likely to be a bad stock.

Although, all stocks follow the same described rules, they differ in the magnitude of price change z. For each stock, z (and consequently -z) is randomly determined once and remains fixed over 60 periods. For example, the value of z may be 6 for one stock (e.g. Stock U (+/- 6)), such that this stock can increase in price by 6 or decrease in price by -6. While for another stock (e.g. Stock W (+/- 10)), the value of z may be 10, such that this stock can increase in price by 10 or decrease in price by -10. Once again, how likely each outcome is, depends on the type of stock (see table). Consequently, **the expected price change of a stock** depends on its type (good or bad) and the magnitude of price change. The expected price change is calculated as 0.7z - 0.3z = 0.4z if you believe the stock is good or 0.3z - 0.7z = -0.4z if you believe the stock is bad.

Comfortably, the computer will do the calculations for you. Once you are asked to **make a return forecast**, the computer will support you by doing the calculations. However, one thing you need to do by yourself, is to decide whether the stock is more likely to be a "good" or a "bad" stock.

In addition to the portfolio return forecast, you will **make an investment decision** in period 30. You will be asked to allocate "fresh" money between Portfolio X and Portfolio Y for the investment horizon of 30 periods (between period 30 and period 60). This investment decision will be payoff-relevant.

Your payment:

You will be paid according to your performance which will be based on your **investment decision**. For the investment decision, you will be endowed with 10,000 ECU which can increase or decrease in value depending on your decision. This means that **you will earn the proportion of the change in portfolio value** between period 30 and period 60 (block 2) given the amount invested in each portfolio (e.g. assume, you invest x% in Portfolio Y which has a total increase in value of 30, you will earn x% of 30). Changes in price of 100 ECU correspond to $ 0.10 (e.g. a portfolio value increase of 150 units corresponds to a 15 cent gain).

Depending on your investment decision, you can gain money which will be added to your fixed payment of $ 1.00.

There is one last important information. We briefly want to make you familiar with the presentation format and then ask you some comprehension questions.

You can see an example of how the performance of the portfolios of stocks is presented to you below. On the left hand side, you can see the performance of Portfolio X and on the right hand side the performance of Portfolio Y. For each stock, we show ...

- the size of the positive and negative return (z and -z) in parentheses (e.g. Stock A (+/-4),
- the number of days with a positive return and the number of days with a negative return,
- and the total value change of the respective stock over 30 periods.

The total value change of each stock can easily be calculated by summing up the product of z times the number of positive return days and -z times the number of negative return days.

On the following page, we will ask you some comprehension questions.

Portfolio X

Stock		Number of positive return days	Number of negative return days	Total change in value
Stock A	(+/-4)			
Stock B	(+/-10)			
Stock C	(+/-6)			
Stock D	(+/-7)			
Stock E	(+/-2)			
Stock F	(+/-5)			
Stock G	(+/-2)			
Stock H	(+/-9)			
Stock I	(+/-6)			
Stock J	(+/-3)			
Total change in portfolio value				

Portfolio Y

Stock		Number of positive return days	Number of negative return days	Total change in value
Stock K	(+/-2)			
Stock L	(+/-3)			
Stock M	(+/-2)			
Stock N	(+/-8)			
Stock O	(+/-5)			
Stock P	(+/-6)			
Stock Q	(+/-1)			
Stock R	(+/-2)			
Stock S	(+/-12)			
Stock T	(+/-1)			
Total change in portfolio value				

Part B: Screenshots of the Experiments

Experiment 1

Figure B-I: Screen with Investment Task

Performance after one month

The tables show the change in value of each stock (in absolute terms) over one month.

Portfolio X	
Stock A	4
Stock B	10
Stock C	-5
Stock D	-7
Stock E	2
Stock F	5
Stock G	2
Stock H	-9
Stock I	5
Stock J	3
Total	10

Portfolio Y	
Stock K	-2
Stock L	-4
Stock M	-2
Stock N	8
Stock O	-5
Stock P	5
Stock Q	-1
Stock R	-2
Stock S	14
Stock T	-1
Total	10

If you had to choose, how would you allocate 1000 US Dollar between portfolio X and portfolio Y?

Amount in portfolio X	
Amount in portfolio Y	
Sum	0

Next

Experiment 3

Figure B-II: Screen with Assessment of Stock Quality

Period 30

Today, you can observe the performance of your investment after one month (from t=0 to t=30).

Portfolio X

Stock		Number of positive return days	Number of negative return days	Total change in value
Stock A	(+/-4)	21	9	48
Stock B	(+/-10)	22	8	140
Stock C	(+/-6)	7	23	-96
Stock D	(+/-7)	8	22	-98
Stock E	(+/-2)	22	8	28
Stock F	(+/-5)	20	10	50
Stock G	(+/-2)	24	6	36
Stock H	(+/-9)	10	20	-90
Stock I	(+/-6)	21	9	72
Stock J	(+/-3)	22	7	42
Total change in portfolio value				132

Portfolio Y

Stock		Number of positive return days	Number of negative return days	Total change in value
Stock K	(+/-2)	3	27	-48
Stock L	(+/-3)	12	18	-18
Stock M	(+/-2)	11	19	-16
Stock N	(+/-8)	24	6	144
Stock O	(+/-5)	8	22	-70
Stock P	(+/-6)	21	9	72
Stock Q	(+/-1)	11	19	-8
Stock R	(+/-2)	11	19	-16
Stock S	(+/-12)	19	11	96
Stock T	(+/-1)	13	17	-4
Total change in portfolio value				132

What are the expected portfolio returns (total expected change in portfolio values) and standard deviation of Portfolio X and Portfolio Y for the next period (t=31)? Based on your evaluation below, the computer will calculate the expected portfolio return and the portfolio standard deviation.

Portfolio X:

Please evaluate for each stock in Portfolio X whether it is more likely to be a good stock (good type) or a bad stock (bad type)?

	Good Type	Bad Type
Stock A	○	○
Stock B	○	○
Stock C	○	○
Stock D	○	○
Stock E	○	○
Stock F	○	○
Stock G	○	○
Stock H	○	○
Stock I	○	○
Stock J	○	○

Portfolio Y:

Please evaluate for each stock in Portfolio Y whether it is more likely to be a good stock (good type) or a bad stock (bad type)?

	Good Type	Bad Type
Stock K	○	○
Stock L	○	○
Stock M	○	○
Stock N	○	○
Stock O	○	○
Stock P	○	○
Stock Q	○	○
Stock R	○	○
Stock S	○	○
Stock T	○	○

Figure B-III: Screen with Investment Task

Period 30

Today, you can observe the performance of your investment after one month (from t=0 to t=30).

Portfolio X

Stock		Number of positive return days	Number of negative return days	Total change in value
Stock A	(+/-4)	21	9	48
Stock B	(+/-10)	22	8	140
Stock C	(+/-6)	7	23	-96
Stock D	(+/-7)	8	22	-98
Stock E	(+/-2)	22	8	28
Stock F	(+/-5)	20	10	50
Stock G	(+/-2)	24	6	36
Stock H	(+/-9)	10	20	-90
Stock I	(+/-6)	21	9	72
Stock J	(+/-3)	22	7	42
Total change in portfolio value				132

Portfolio Y

Stock		Number of positive return days	Number of negative return days	Total change in value
Stock K	(+/-2)	3	27	-48
Stock L	(+/-3)	12	18	-18
Stock M	(+/-2)	11	19	-16
Stock N	(+/-8)	24	6	144
Stock O	(+/-5)	8	22	-70
Stock P	(+/-6)	21	9	72
Stock Q	(+/-1)	11	19	-8
Stock R	(+/-2)	11	19	-16
Stock S	(+/-12)	19	11	96
Stock T	(+/-1)	13	17	-4
Total change in portfolio value				132

You are endowed with "fresh" money of 10,000 ECU. For a new investment of 30 periods, how do you want to allocate 10,000 ECU between Portfolio X and Portfolio Y?

Portfolio X	
Portfolio Y	
Sum	0

Part C: Portfolio Expected Return and Standard Deviation

Portfolios in Experiment 2 and 3 are designed such that (i) the expected portfolio return and (ii) the standard deviation of portfolio returns are identical. We calculate expected returns and standard deviation using the standard formulas.

$$\mu_P = \sum_{i=1}^{n} w_i \mu_i$$

$$\sigma_P^2 = \sum_{i=1}^{n} w_i^2 \sigma_i^2 + \sum_{i=1} \sum_{i \neq j} w_i w_j Cov(i,j)$$

The expected return and the standard deviation of individual stocks are calculated based on these formulas:

$$\mu_S = p_i X_i + (1 - p_i)(-X_i)$$

$$\sigma_S^2 = p_i (X_i - \mu)^2 + (1 - p_i)(X_i - \mu)^2$$

Table C-I show the values for the two portfolios in Experiment 3.

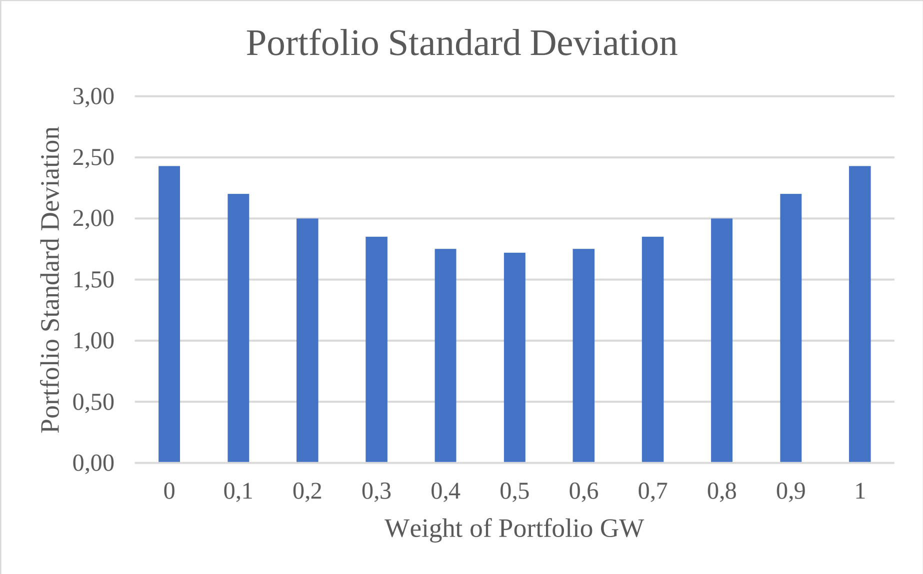
Table C-I: Portfolio Expected Return and Standard Deviation

Portfolio GW									
Stock	Return (More Likely)	High Return	Low Return	P (High Return)	P (Low Return)	E(Return)	Var(Return)	Std Deviation (Return)	Weight
A	4	4	-4	0.7	0.3	1.60	35.69	5.97	0.1
B	10	10	-10	0.7	0.3	4.00	221.50	14.88	0.1
C	-6	6	-6	0.3	0.7	-2.40	34.83	5.90	0.1
D	-7	7	-7	0.3	0.7	-2.80	47.15	6.87	0.1
E	2	2	-2	0.7	0.3	0.80	9.15	3.02	0.1
F	5	5	-5	0.7	0.3	2.00	55.60	7.46	0.1
G	2	2	-2	0.7	0.3	0.80	9.15	3.02	0.1
H	-9	9	-9	0.3	0.7	-3.60	77.49	8.80	0.1
I	6	6	-6	0.7	0.3	2.40	79.93	8.94	0.1
J	3	3	-3	0.7	0.3	1.20	20.21	4.50	0.1
Portfolio						4		24.3	

Portfolio GL									
Stock	Return (More Likely)	High Return	Low Return	P (High Return)	P (Low Return)	E(Return)	Var(Return)	Std Deviation (Return)	Weight
K	-2	2	-2	0.3	0.7	-0.80	4.49	2.12	0.1
L	-3	3	-3	0.3	0.7	-1.20	9.23	3.04	0.1
M	-2	2	-2	0.3	0.7	-0.80	4.49	2.12	0.1
N	8	8	-8	0.7	0.3	3.20	141.87	11.91	0.1
O	-5	5	-5	0.3	0.7	-2.00	24.40	4.94	0.1
P	6	6	-6	0.7	0.3	2.40	79.93	8.94	0.1
Q	-1	1	-1	0.3	0.7	-0.40	1.65	1.28	0.1
R	-2	2	-2	0.3	0.7	-0.80	4.49	2.12	0.1
S	12	12	-12	0.7	0.3	4.80	318.83	17.86	0.1
T	-1	1	-1	0.3	0.7	-0.40	1.65	1.28	0.1
Portfolio						4		24.3	

Based on these two investment opportunities (the two portfolios), we can determine the variance of a combination (i.e. a portfolio of portfolios) as a function of how much individuals invest in each portfolio. Figure C-I present the findings.

Figure C-I: Portfolio Standard Deviation



The highest Sharpe ratio (i.e. expected return per unit of risk) is achieved by investing 50% in Portfolio GW and 50% in Portfolio GL.

Part D: Additional Analyses

Figure D-I: Satisfaction in Experiment 1 (Additional Treatments)

7: high for the four portfolio pairs $G_pW_S - L_pW_S$, $G_pL_S - L_pL_S$, $G_pW_S - L_pL_S$ and $G_pL_S - L_pW_S$. The blue bars refer to the portfolios with a positive overall return and the red bars refer to portfolios with a negative overall return. Results are separately shown for treatments in which portfolio returns are not displayed and for treatments in which portfolio returns are displayed. Displayed are 95%-confidence intervals.

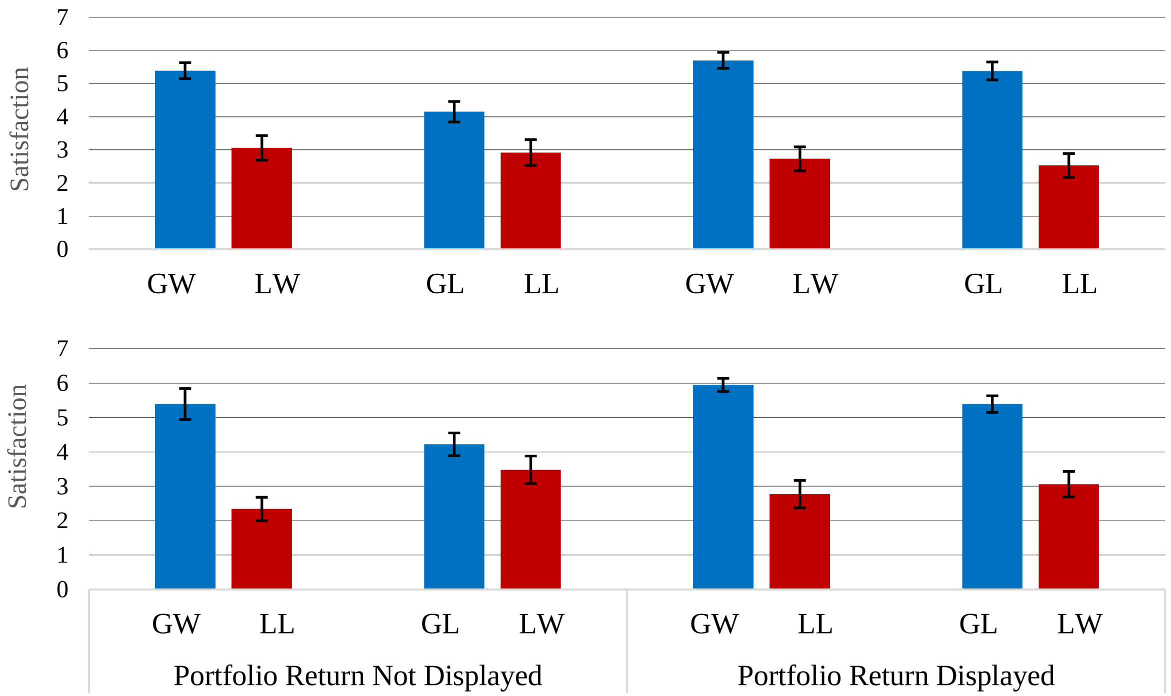


Figure D-II: Return Expectations in Experiment 1 (Additional Treatments)

7: high for the four portfolio pairs $G_pW_S - L_pW_S$, $G_pL_S - L_pL_S$, $G_pW_S - L_pL_S$ and $G_pL_S - L_pW_S$. The blue bars refer to the portfolios with a positive overall return and the red bars refer to portfolios with a negative overall return. Results are separately shown for treatments in which portfolio returns are not displayed and for treatments in which portfolio returns are displayed. Displayed are 95%-confidence intervals.

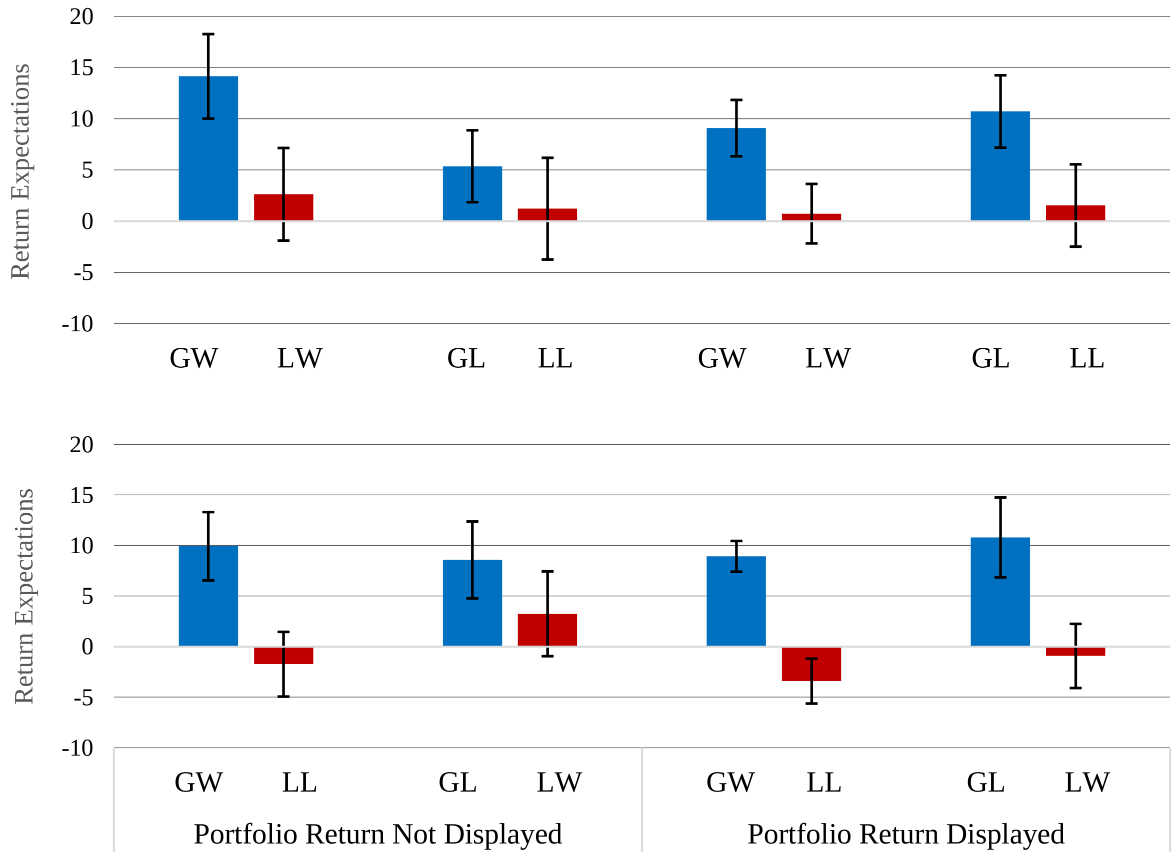


Figure D-III: Risk Perception in Experiment 1 (Additional Treatments)

high for the four portfolio pairs $G_pW_S - L_pW_S$, $G_pL_S - L_pL_S$, $G_pW_S - L_pL_S$ and $G_pL_S - L_pW_S$. The blue bars refer to the portfolios with a positive overall return and the red bars refer to portfolios with a negative overall return. Results are separately shown for treatments in which portfolio returns are not displayed and for treatments in which portfolio returns are displayed. Displayed are 95%-confidence intervals.

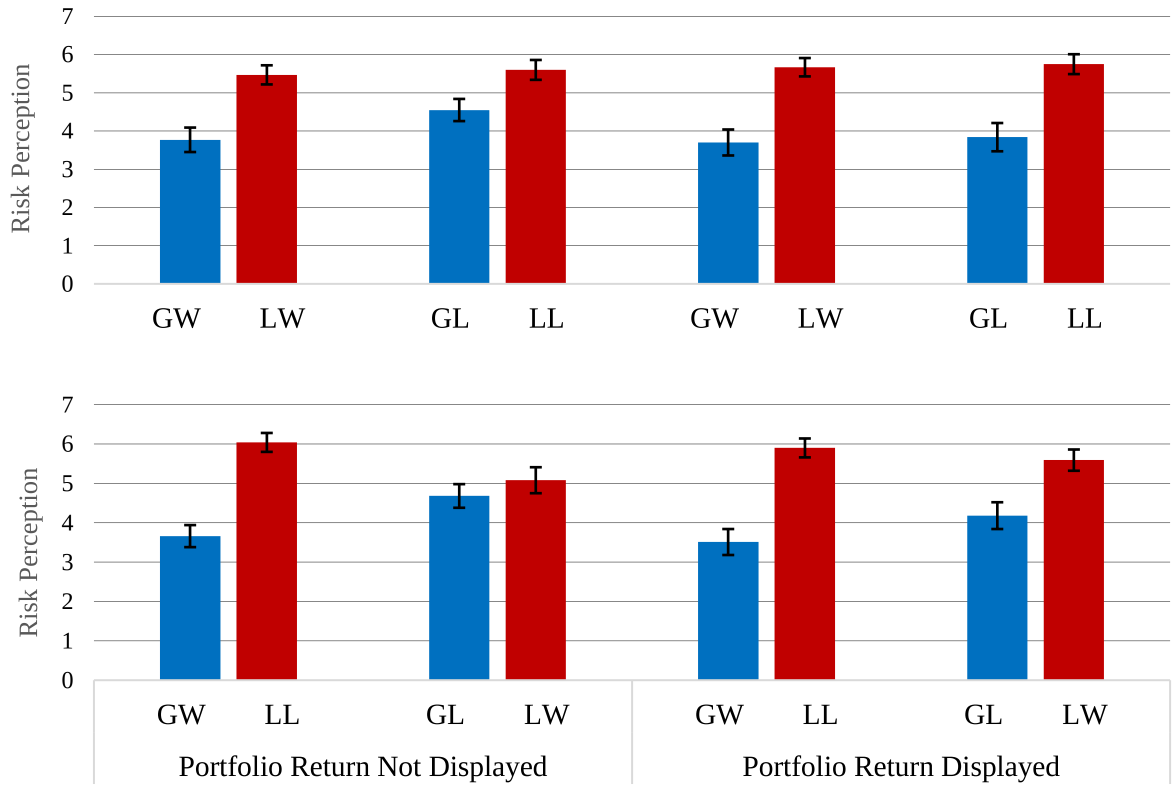


Figure D-IV: Investment in Experiment 2 Conditional on Return Expectations (Additional Treatments)

same expected returns for the two portfolios of a pair. The portfolio pairs are $G_p W_S - L_p W_S$, $G_p L_S - L_p L_S$, $G_p W_S - L_p L_S$ and $G_p L_S - L_p W_S$. The blue bars refer to the portfolios with a positive overall return and the red bars refer to portfolios with a negative overall return. Displayed are 95%-confidence intervals.

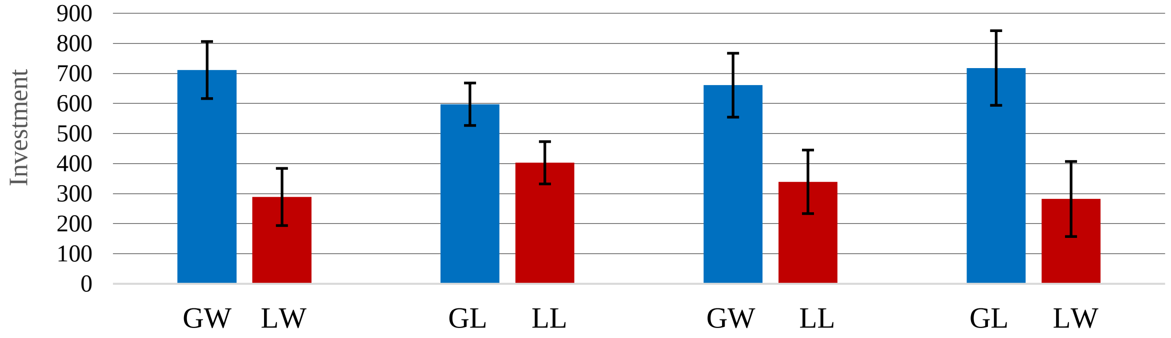


Figure D-V: Risk Perception in Experiment 2 (Additional Treatments)

high for the four portfolio pairs $G_pW_S - L_pW_S$ and $G_pL_S - L_pL_S$ (Panel A) and $G_pW_S - L_pL_S$ and $G_pL_S - L_pW_S$ (Panel B). The blue bars refer to the portfolios with a positive overall return and the red bars refer to portfolios with a negative overall return. Results are separately shown for treatments in which portfolio returns are not displayed and for treatments in which portfolio returns are displayed. Displayed are 95%-confidence intervals.

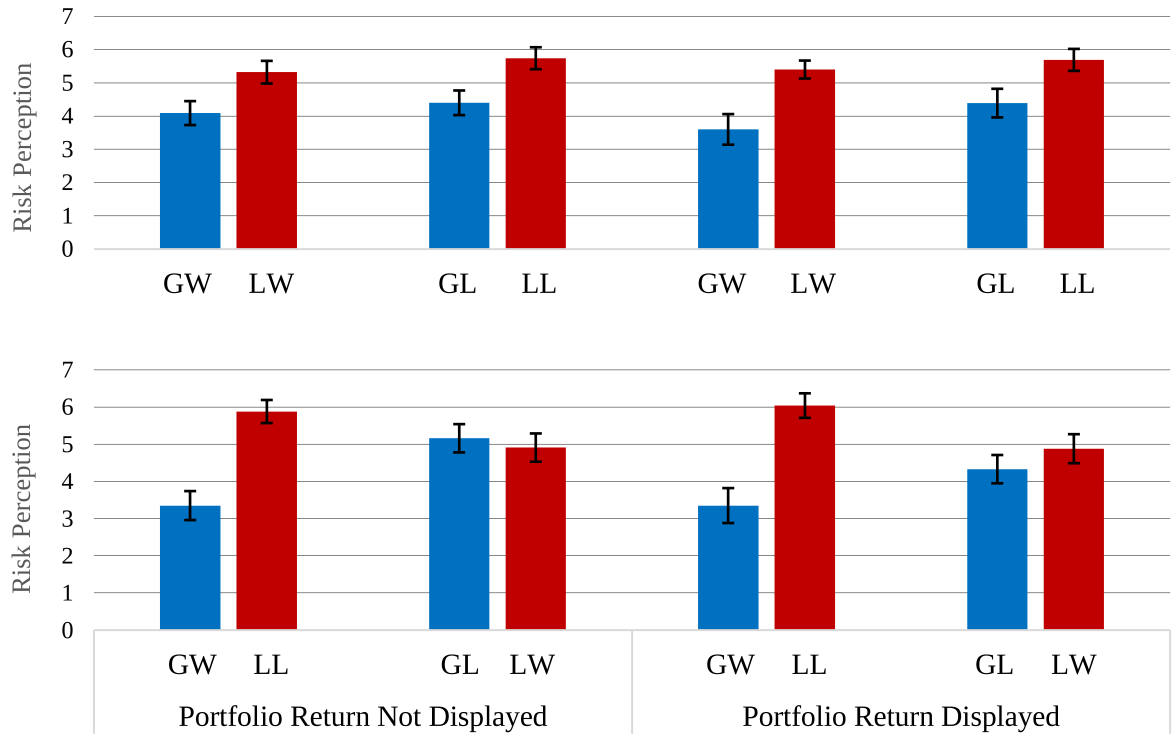
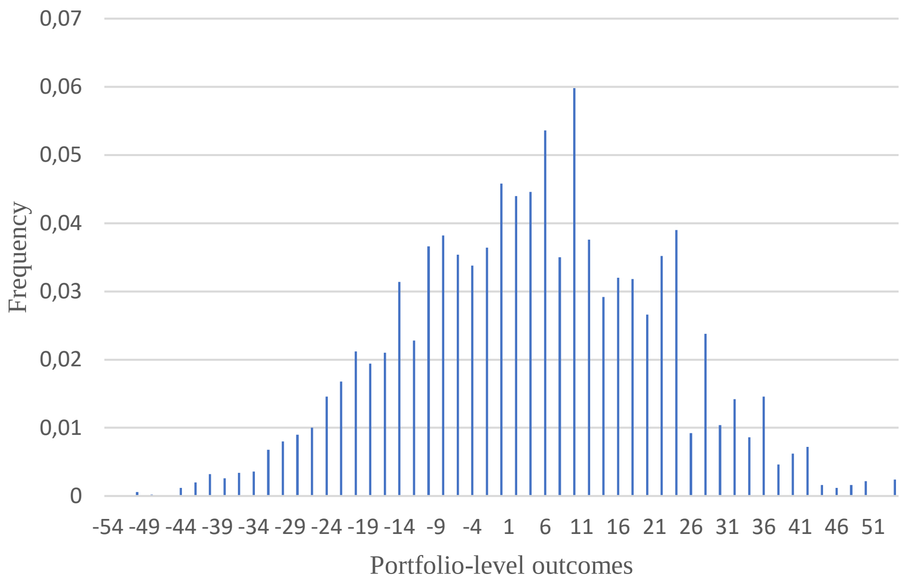


Figure D-VI: Simulation of Portfolio-level Outcomes

This figure illustrates the simulated probability distribution function of portfolio-level outcomes for the gain-winner portfolio (Panel A) as well as the gain-loser portfolio (Panel B) using 10,000 independent iterations.

Panel A: Portfolio GW



Panel B: Portfolio GL

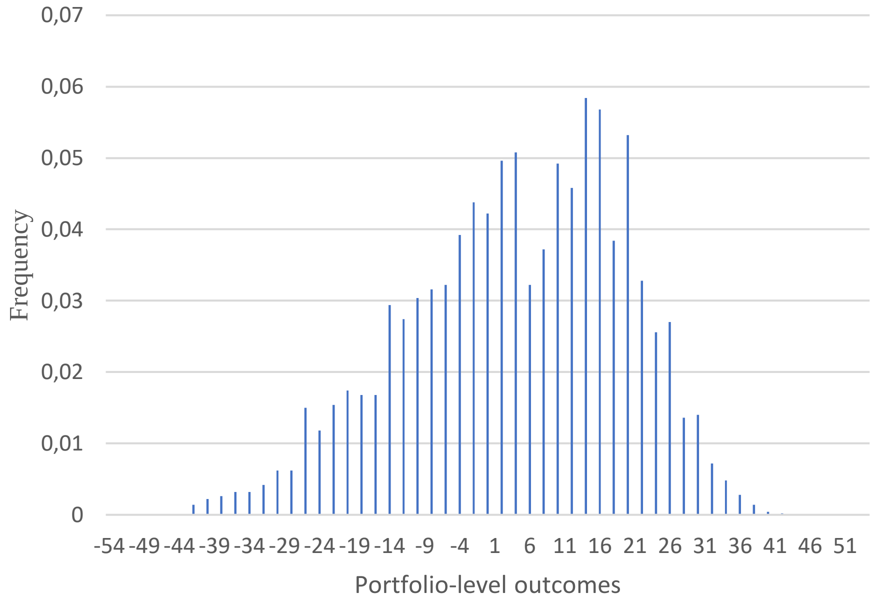


Table D-I: Regression Results of Satisfaction (Experiment 1)

The table shows the coefficients of OLS regressions of satisfaction on a gain dummy variable (1 if portfolio trades at a gain), a winner dummy variable (1 if portfolio has more winner than loser assets), the interaction term of gain and winner, a display dummy variable (1 if total portfolio return is displayed) and multiple interaction terms of the display, gain and winner dummy variable. Regression (1) is on the entire sample, regression (2) on the subsample when total portfolio return is displayed and regression (3) when it is not displayed, regression (4) is on the entire sample and controls for whether total portfolio return is displayed or not. We cluster standard errors on the individual investor level and on the portfolio pair level, standard errors are reported in parentheses, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	*Satisfaction*			
	Entire sample (1)	Total value displayed (2)	Total value not displayed (3)	Entire sample (4)
Gain	1.860***	2.455***	1.264***	1.264***
	(0.103)	(0.142)	(0.139)	(0.139)
Winner	0.645***	0.446***	0.843***	0.843***
	(0.0996)	(0.141)	(0.140)	(0.140)
Gain x Winner	0.264**	0.0950	0.434**	0.434**
	(0.124)	(0.170)	(0.172)	(0.171)
Display				-0.124
				(0.156)
Display x Gain				1.190***
				(0.199)
Display x Winner				-0.397**
				(0.199)
Display x Gain x Winner				-0.339
				(0.241)
Constant	2.715***	2.653***	2.777***	2.777***
	(0.0782)	(0.112)	(0.109)	(0.109)
Observations	1,936	968	968	1,936
R^2	0.318	0.408	0.263	0.345

Table D-II: Regression Results of Risk Perception (Experiment 1)

The table shows the coefficients of OLS regressions of risk perception on a gain dummy variable (1 if portfolio trades at a gain), a winner dummy variable (1 if portfolio has more winner than loser assets), the interaction term of gain and winner, a display dummy variable (1 if total portfolio return is displayed) and multiple interaction terms of the display, gain and winner dummy variable. Regression (1) is on the entire sample, regression (2) on the subsample when total portfolio return is displayed and regression (3) when it is not displayed, regression (4) is on the entire sample and controls for whether total portfolio return is displayed or not. We cluster standard errors on the individual investor level and on the portfolio pair level, standard errors are reported in parentheses, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	*Risk Perception*			
	Entire sample	Total value displayed	Total value not displayed	Entire sample
	(1)	(2)	(3)	(4)
Gain	-1.184***	-1.397***	-0.971***	-0.971***
	(0.0870)	(0.130)	(0.114)	(0.114)
Winner	-0.386***	-0.256**	-0.517***	-0.517***
	(0.0766)	(0.102)	(0.114)	(0.114)
Gain x Winner	-0.355***	-0.314*	-0.397**	-0.397**
	(0.117)	(0.167)	(0.163)	(0.163)
Display				0.0537
				(0.113)
Display x Gain				-0.426**
				(0.173)
Display x Winner				0.260*
				(0.153)
Display x Gain x Winner				0.0826
				(0.233)
Constant	5.676***	5.702***	5.649***	5.649***
	(0.0565)	(0.0810)	(0.0789)	(0.0789)
Observations	1,936	968	968	1,936
R^2	0.221	0.246	0.206	0.228

Table D-III: Regression Results of Return Expectations (Experiment 1)

The table shows the coefficients of OLS regressions of return expectations on a gain dummy variable (1 if portfolio trades at a gain), a winner dummy variable (1 if portfolio has more winner than loser assets), the interaction term of gain and winner, a display dummy variable (1 if total portfolio return is displayed) and multiple interaction terms of the display, gain and winner dummy variable. Regression (1) is on the entire sample, regression (2) on the subsample when total portfolio return is displayed and regression (3) when it is not displayed, regression (4) is on the entire sample and controls for whether total portfolio return is displayed or not. We cluster standard errors on the individual investor level and on the portfolio pair level, standard errors are reported in parentheses, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	*Return Expectations*			
	Entire sample (1)	Total value displayed (2)	Total value not displayed (3)	Entire sample (4)
Gain	7.068***	8.926***	5.188***	5.188***
	(1.086)	(1.371)	(1.685)	(1.684)
Winner	2.654**	1.210	4.116**	4.116**
	(1.098)	(1.409)	(1.677)	(1.677)
Gain x Winner	0.142	-1.024	1.380	1.380
	(1.359)	(1.630)	(2.180)	(2.179)
Display				-1.338
				(1.827)
Display x Gain				3.738*
				(2.172)
Display x Winner				-2.906
				(2.190)
Display x Gain x Winner				-2.404
				(2.721)
Constant	1.000	0.333	1.671	1.671
	(0.913)	(1.203)	(1.375)	(1.375)
Observations	1,533	774	759	1,533
R^2	0.055	0.088	0.044	0.063

Table D-IV: Portfolio Composition and Fund Flows – Daily Data with 5 Lags

The table summarizes results of panel regressions of the dependent variable *Fund Flow* on day t on *Portfolio Composition* on day t and up to five days lagged and *Fund Return* on day t and up to five days lagged. We use fund and day fixed effects and double-cluster standard errors on the index and day level, t-statistics are reported in parentheses, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	*Fund Flow t*			
	(1)	(2)	(3)	(4)
Composition t			0.000284	0.000474
			(1.70)	(1.69)
Composition t-1	0.000305*	0.000194	0.000331**	0.000226
	(2.70)	(1.74)	(3.24)	(2.15)
Composition t-2	0.000559**	0.000514**	0.000580**	0.000524**
	(4.32)	(4.21)	(4.49)	(4.31)
Composition t-3	0.000370*	0.000340*	0.000381*	0.000360*
	(3.06)	(2.56)	(3.02)	(2.60)
Composition t-4	0.000395	0.000428	0.000398*	0.000441
	(2.29)	(2.20)	(2.35)	(2.33)
Composition t-5	-0.0000506	-0.0000629	-0.0000811	-0.0000664
	(-0.45)	(-0.46)	(-0.71)	(-0.48)
Fund Return t				-0.0111
				(-1.65)
Fund Return t-1		0.00552*		0.00355
		(2.53)		(1.78)
Fund Return t-2		0.00380*		0.00344*
		(2.85)		(2.50)
Fund Return t-3		0.00154		0.00125
		(0.95)		(0.82)
Fund Return t-4		-0.000715		-0.000925
		(-0.48)		(-0.62)
Fund Return t-5		-0.000911		-0.00102
		(-0.71)		(-0.77)
Constant	-0.000680**	-0.000593**	-0.000836**	-0.000865**
	(-4.26)	(-3.30)	(-4.83)	(-3.38)
Observations	88686	84542	88510	84386
R^2	0.042	0.040	0.041	0.040
Fund FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES