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The Portfolio Composition Effect

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Abstract

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JEL Classification: G11, G12, G40, D84

Keywords: Portfolio composition, investment behavior, risk preferences, Mental accounting

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The Portfolio Composition Effect[*]

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June, 2021

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This study asks whether a simple, counting-based measure of performance, which is the fraction of winner stocks in a portfolio, affects people's 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.

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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 investor's trading 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 tough, these studies consistently show that investors do not form optimal portfolios, the portfolio is a relevant and important component to investor behavior in multiple ways: 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 they show that the portfolio value affects people's 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 a portfolio level, this form of stock-by-stock accounting results in varying compositions of "good" and "bad" investment episodes 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.

[1] For individuals' 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). For individuals' belief formation about a risky asset, various studies document behavioral biases such as base-rate neglect, prior-biased inference, overconfidence, and over-extrapolation from recent signals (see Benjamin, 2019 for a recent review).

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 invest in a portfolio depends on the portfolio's composition of winner and loser stocks. When seeing two portfolios with the same realized overall return, people allocate significantly more funds to those portfolios with a larger fraction of winner stocks than to alternative portfolios 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 that this is indeed the case.

Why should the composition of winner and loser stocks in a portfolio matter in the first place? Literature in cognitive psychology suggest 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 whereby they distinguish between "winner" and "loser" stocks, and it assumes that they 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 have shown 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, or 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 than about its actual size.

Based on 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 engage in a "semi-joint" evaluation of individual stock outcomes. This means, they assign stocks in their distinct mental accounts to either a "winner" category or a "loser" category which might arguably be the most salient difference between them. Given the complexity of full integration and individuals' reluctance to integrate outcomes across different mental accounts, they simply engage in a counting heuristic to evaluate a portfolio investment decision. This is they count the number of mental accounts (i.e. stocks) which are assigned either to the "winner" or the "loser" category, compare these values to one another, and 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 almost 1200 subjects have to make several portfolio investment decisions. In chronological order, we first 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 participants' 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 even in this setting, the fraction of winner stocks drives participants' investments 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.

Taken together, we show experimentally that a portfolio's composition of winner and loser stocks affects an investor's willingness to invest in a portfolio. Specifically, this effect persists when investors' beliefs about expected returns and 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).

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 index' composition 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-determined portfolios with respect to the index' members over time. Moreover, market indices capture a lot of attention in the media and press of the respective country since they are often referred to as indicators of a country's economy.

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 (e.g. 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. (2019) who find that the portfolio's overall return affects individual stock selling behavior (e.g. the portfolio-driven disposition effect). While the focus of our paper is on the overall portfolio evaluation rather than the individual stock investment, our findings suggest that a crucial determinant for the evaluation of the overall portfolio performance is the portfolio's composition of winner and loser stocks. We provide evidence that investors evaluate the overall portfolio value differently given the portfolio's fraction of winner and loser stocks. 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, namely pre-determined portfolios, it becomes important to examine how investors evaluate portfolios and choose among them. Our findings suggest that the performance of the portfolio's 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 posterior beliefs about an asset's underlying quality (see Benjamin, 2019 for a review). Much 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' evaluation of the portfolios' risk. This finding is consistent with Slovic and Lichtenstein (1968), Anzoni and Zeisberger (2017), Holzmeister et al. (2020) and Zeisberger (2020), who propose and test alternative risk measures such as an asset's probability of loss that people are actually concerned about when making risky choices. 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 portfolio's probability 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. 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 "categorical thinking is a natural and inevitable tendency of the human mind" (p. 171). A 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 that are 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 one and 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 mental accounts and hence stocks are assigned to one of two distinct categories, namely "winner" stocks or "loser" stocks. Given that the 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.

To test our framework and as such the effect of a portfolio's composition of winner and 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] Stocks with zero return are not included in the measure. In the following, we will refer to this composition measure as “fraction of winners”. Based on the proposed framework, we predict that participants invest more in portfolios with larger fractions of winner stocks, holding overall *realized portfolio returns* constant.

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 this is indeed the case. 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 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 may easily gain an impression of a portfolio’s composition of winner and loser stocks. 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.

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

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 number of stocks that were “advancing” (i.e. winner stocks), “declining” (i.e. loser stocks), and “unchanged”. For various equity market indices, the financial website onvista depicts the fraction of “Top Stocks” (i.e. winners) and “Flop Stocks” (i.e. losers) of an index in a pie chart close to the overall index performance (see Figure 1).

2. Experimental Evidence

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 when forming beliefs about the underlying quality of stocks is possible and easy. To implement this, we conduct three investment experiments in which participants are asked to allocate an endowment between two portfolios which both consist of ten different and equally-weighted stocks. 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 and thus the freedom they have when forming beliefs. In essence, this approach will allow us to explore beliefs as an underlying channel of the effect.

A. Treatments

We start with design feature (1). Portfolios are constructed along two dimensions. 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. The “winner” portfolio composition (W_S) consists of seven winner (i.e. positive realized return) and three loser (i.e. negative realized return) stocks. The “loser” portfolio composition (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.[4] The second treatment dimension of our experimental design 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).[5] We combine the two treatment dimensions to generate different *portfolios*. The following four *portfolios* result from

[4] We keep the cross-sectional variance of stock returns identical across portfolios to avoid a large heterogeneity in the size of returns across portfolios.
[5] 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_pW_S, G_pL_S, L_pW_S, and L_pL_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. participants' allocation decisions between two portfolios, we combine two *portfolios* to one *portfolio pair*. Treatments are then defined by portfolio pairs which in turn are defined by the differences in the respective treatment dimensions. An overview of all treatments is provided in Table 1. For the moment, we will focus on the two portfolio pairs $G_pW_S - G_pL_S$ and $L_pW_S - L_pL_S$. 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 portfolio investment decisions.

Figure 2 demonstrates how *portfolio pairs* are presented to participants. Exemplary, the portfolio pair $G_pW_S - G_pL_S$ is shown. Both portfolios have the same realized positive return. However, portfolio G_pW_S has a larger fraction of winner stocks than portfolio G_pL_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).[6]

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 ($G_pW_S - G_pL_S$ with portfolio returns displayed, $G_pW_S - G_pL_S$ without portfolio returns displayed, $L_pW_S - L_pL_S$ with portfolio returns displayed, and $L_pW_S - L_pL_S$ without

[6] 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.

portfolio returns displayed). We run all of these treatments in experiment one and two. In experiment three, we only run the treatment $G_p W_S - G_p L_S$ with portfolio returns displayed, but conduct two different conditions with respect to whether the portfolio variance is explicitly displayed in addition to the expected portfolio returns.

B. The Return Generating Process

How are stock returns generated? This section describes how design features (2) and (3), a normative benchmark and a learning environment, are implemented. The return generating process used in our experiments is a Bayesian updating task motivated by Grether (1980). There are two types of stocks, "good" stocks that draw returns from a good distribution and "bad" stocks 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.

At the beginning of the experiment, participants do not know whether a stock draws from the good or bad distribution, i.e. it is equally likely that a stock draws 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. Over the course of the experiment, participants observe stock return realizations from which they can infer a stock's underlying 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. The computer helps subjects in doing the calculations. In particular, subjects are asked to assess a stock's quality and then, based on the assessment, the computer calculates the expected return of the stock. 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.[7]

Besides expected returns, we design portfolios such that the portfolio return volatility (i.e. the variance of portfolio returns) is also identical across portfolios. In other words, we ensure 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,

[7] Instructions and comprehension questions can be read in Appendix A.

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.[8]

C. Experimental Procedure and Participants

In all experiments, there are two periods framed as months: a learning period and an investment period. Participants are told that they have invested \$1000 in each of two equally weighted portfolios of stocks at the beginning of the learning period one month ago (at $t = -1$). Today (at $t = 0$), they can learn about the performance of their portfolios over the last month and can then make an investment decision (i.e. they allocate new cash of \$1000 between the two portfolios) for another one-month investment period (till $t = 1$).[9] At the end of the investment period, all returns are realized and paid out.[10] Besides the investment decision, we elicit additional variables: We ask participants to estimate the expected portfolio return and to assess the riskiness of the portfolio.[11] Screenshots of the experiments can be seen in Appendix B.

The degree to which subjects can learn about the data generating process differs across experiments. In experiment one, we do not tell participants the underlying data generating process of stock returns. Participants are presented one return realization per stock and period, and can then, based on this information, form beliefs about expected returns. In experiment two and three, we do tell participants the underlying data generating process and test their understanding of how they can infer and calculate a stocks' expected return. In experiment two, we keep number of return realizations identical to experiment one to allow direct comparisons. In experiment three, we increase the number of return realizations to thirty per stock and period. This extension of the design ensures that the uncertainty about a stock's underlying distribution is almost completely reduced. As such, after observing thirty return realizations per stock, participants can be sure about the stocks' underlying distribution and the resulting expected stock and portfolio returns. Since we provide participants in experiment three with more return

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[8] More details are provided in Appendix C.

[9] In experiment one, each participant makes investment decisions for two pairs of portfolios one after the other in randomized order. In experiment two and three, each participant makes investment decisions for one portfolio pair. We reduced the pairs of portfolios per participant in experiment 2 because we wanted to make sure that the overall time spent on experiment 2 including the calculations on expected returns should not take significantly longer than experiment 1.

[10] The endowment in experiment 3 is \$10000 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.

[11] In experiment one, we also ask participants about their satisfaction with the performance of the portfolio.

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 clearly explain to participants that returns are presented as absolute changes in value and that portfolios are rebalanced at the end of the learning period to ensure equal weights of stocks when participants make the investment decision.

1193 participants were recruited from a large crowdsourcing platform called Amazon Mechanical Turk (MTurk). 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). 61% (66%, 68%) of the participants in experiment one (two, three) were male and the mean age of all participants was 34.7 years (33.9 years, 32.6 years).

2.1 Results of Experiment 1: The Portfolio Composition Effect

In experiment one we test the effect of varying fractions of winners in a portfolio on portfolio investment decisions. We start by comparing investments in portfolios that have realized identical portfolio returns, but differ in the fraction of winner stocks (baseline treatments).

Figure 4 Panel A shows the average investments in each portfolio. The blue bars show the average investment associated with portfolios that have a larger fraction of winners (70% winners/30% losers). The red bars show the average investment associated with portfolios that have a larger fraction of losers (30% winner/70% losers). Results are split by overall portfolio return (G: same positive return, L: same negative return) and whether the portfolio return is displayed or not. Indicated are 95%-confidence intervals. We begin by discussing the results of the treatments in which the overall portfolio return is not explicitly displayed. 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 ($t(77)=6.24$, $p<0.001$) 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 ($t(77)=4.22$, $p<0.001$) more in the portfolio with more winners.

Is the larger investment in portfolios with more winner stocks due to the fact that it is not obvious to participants that both portfolios have identical realized returns? To test this, we run the baseline treatments again and clearly display overall portfolio returns. In similar magnitude and significance, we also find a strong portfolio composition effect for these treatments. If both portfolios have realized the same positive return and this information is clearly displayed, participants invest on average \$258 out of \$1000 ($t(78)=6.37$, $p<0.001$) more in the portfolio with the larger fraction of winners. If both portfolios realized the same negative return and this portfolio return is clearly displayed, participants invest on average \$224 ($t(78)=5.12$, $p<0.001$) more in the portfolio with the larger fraction of winners. As such, we can confidentially rule out that the effect depends on whether the portfolio return is displayed.

Besides the investment, we also elicit participants' satisfaction with the performance of the portfolios (Panel B), their beliefs about expected portfolio returns (Panel C) and risk (Panel D). We find that all of these variables are consistent with participants' investment decisions. 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. 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 perceptions 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, these findings suggest a robust and significant effect of a portfolio's 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.

2.2 Results of Experiment 2: Learning About Expected Returns I

The previous section presented that the portfolio's fraction of winners affects the willingness to invest in the portfolio. We now examine a potential driver underlying the effect. In particular, we aim to test whether the effect still exists, when we keep not only realized returns, but also expected returns identical across portfolios.

Figure 5 displays the results. We start by comparing the average investments in each portfolio unconditional of participants' stated beliefs in Panel A. Average investments are again split by portfolio returns and whether portfolio returns are displayed or not. 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 ($t(50)=6.62$, $p<0.001$; $t(49)=7.25$, $p<0.001$). 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 ($t(54)=4.46$, $p<0.001$; $t(40)=4.74$, $p<0.001$).

To test whether the effect still persists if subject's beliefs about expected portfolio returns are identical, we rerun the analysis on the subsample of subjects who report – as Bayes' rule implies – the same expected returns for both portfolios. Even though, the sample size decreases with this restriction, we find for those participants who report exactly the same beliefs about expected portfolio returns, a portfolio composition effect. Figure 5 Panel B reports the average investment for this subsample.[12] If portfolios have the same positive realized return and participants report the same expected portfolio returns, we find that they invest on average \$356 more in the portfolio with more winners ($t(35)=4.38$, $p<0.001$). If portfolios have the same negative realized return and participants report the same expected portfolio returns, we find that they invest on average \$254 more in the portfolio with more winners ($t(34)=3.60$, $p=0.001$).

We also elicit participants' risk assessments. Panel C reports the findings. Participants rate those portfolios which consist of more loser stocks to be riskier than those portfolios which consist of more winner stocks. This result is consistent with their investment decision and replicates findings from experiment one.

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

2.3 Results of Experiment 3: Learning About Expected Returns II

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 modification allows us to test whether the documented effect still exists if subjects' beliefs about expected portfolio returns and their beliefs about volatility should be identical across portfolios.

Figure 6 Panel A reports the average investment in each portfolio pooled and split by whether the portfolio volatility is displayed. Unconditional of participants' beliefs about expected returns, we find a strong effect. Participants invest on average \$2994 (out of \$10000) more in the portfolio which consists of more winner than loser stocks ($t(101)=7.86$, $p<0.001$). This finding is independent of whether the portfolio variance is displayed or not. Panel B displays the results for those participants who report subjective expected returns that are identical to the objective expected returns of Bayes.[13] They invest on average \$4295 (out of \$10000) more in the portfolio with more winners ($t(58)=9.49$, $p<0.001$). Again, and interestingly, 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 participants' beliefs about 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 Panel C displays the average risk assessments unconditional of subjects' beliefs about expected portfolio returns and volatility and Panel D 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 stocks to be less risky ($t(102)=9.55$, $p<0.001$). 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 ($t(58)=11.77$, $p<0.001$).

[13] 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.

2.4 Further Experimental Results

So far, the analysis focused on portfolios that have the same overall realized/expected return, but differ in the fraction of winners. Now, we examine the results of the four additional treatments we ran in experiment one and two (see Table 1). The additional treatments allow us to further test the robustness of the portfolio composition effect. In particular, we can analyze situations in which portfolios have the identical fraction of winners and differ in the overall realized (expected) portfolio return ($G_pW_S - L_pW_S$ and $G_pL - L_pL_S$) and situations in which, we can differ both, the fraction of winners and the overall realized (expected) portfolio return ($G_pW_S - L_pL_S$ and $G_pL_S - L_pW_S$).

In greater detail, we will provide answers to the following questions: (1) How strong is the effect of differences in the fraction of winners on investment decisions as compared to the effect of differences in overall realized and expected portfolio returns? (2) How does "consistent" performance information (the portfolio with a positive realized return consists of a high fraction of winner stocks and the portfolio with a negative realized return consists of a high fraction of loser stocks) affect investment decisions as compared to "inconsistent" performance information (the portfolio with a positive realized return consists of a high fraction of loser stocks, while the portfolio with a negative realized return consists of a high fraction of winner stocks)?

Figure 7 Panel A and Panel B display the average investment in each portfolio for the four additional treatments in experiment one and two, respectively. First, we find for those treatments in experiment one (experiment two) in which we keep the fraction of winners constant and differ the overall realized (expected) portfolio return (i.e. $G_pW_S - L_pW_S$ and $G_pL - L_pL_S$) that participants invest on average \$550 (\$494) more in the portfolio with a positive realized (and a positive expected) return than in the alternative portfolio with a negative realized (and a negative expected) return. This difference is neither affected by whether both portfolios consist of a high fraction of winner stocks or whether both portfolios consist of a high fraction of loser stocks nor by whether the portfolio return is displayed or not.

Second, we provide further evidence of the portfolio composition effect by comparing differences between the portfolio pairs $G_pW_S - L_pL_S$ and $G_pL_S - L_pW_S$. Across both portfolio pairs, 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). As an alternative test of the portfolio composition effect, we compare differences in investment across two portfolio pairs instead of the investment between two portfolios within one portfolio pair (see baseline treatments). 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 ($Investment_{G_pW_S} - Investment_{L_pL_S} = Investment_{G_pL} - Investment_{L_pW_S}$). However, we find significant differences in investment. In particular, participants in experiment one (experiment two) invest on average \$633 (\$583) more in portfolio G_pW_S than in portfolio L_pL_S. This difference in investment reduces significantly by \$171 (t(83)=3.60, p<0.001; \$279, t(95)=3.50, p<0.001) to \$462 (\$304) for the portfolio pair $G_pL_S - L_pW_S$. It is particularly interesting that the difference in investment becomes smallest with \$146 (t(78)=2.53, p=0.02) and is only significant at the 5% level for the portfolio pair $G_pL_S - L_pW_S$ if the portfolio returns are not displayed. Then, if participants do not instantly know the portfolio return, it seems as if they offset actually low portfolio returns with the positive impression from a high fraction of winners. In other words, they seem to falsely infer an overall positive performance of the portfolio from the high fraction of winner stocks and thus they invest quite a bit in the portfolio L_pW_S. However, if they are told the overall portfolio return, they go back to investing much less in the portfolio L_pW_S. Taken together, there is a common finding: the fraction of winners affects participants' portfolio investment decisions. Holding the overall realized and expected return constant, a larger fraction of winners results in a greater investment.

To conclude our experimental findings, 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.[14]

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

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

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

[14] 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.

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 2 reports the results for each experiment individually. In both experiments, we find a strong 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.

Like in the baseline treatments, we find that participants' self-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).

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 index' 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 are often referred to as indicators of a country's overall economic condition. 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.[15]

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.

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[15] For example, the WSJ reports for US Stocks in its Markets Diary Section the number of stocks that were "advancing" (i.e. winner stocks), "declining" (i.e. loser stocks), and "unchanged". Similarly, financial websites such as finanzen.net or onvista.com report for leading market indices the number of "top stocks" and "flop stocks". 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.

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 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. Our paper contributes to the literature of ETF investor return-chasing behavior.

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 3.

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 ETF provider’s website.

We obtain fund-level data from Morningstar. For each ETF (identified by its SecId and FundId), we download the ETF’s 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 day TNAs adjusted for the respective day’s index return.[16] For the calculation of our main

[16] 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

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 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 4 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 4 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.[17]

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):

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

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

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 winner stocks of ETF i on index j on day $t-l$, where l represents the number of lags.[18] 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 5.

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 today's fund flows of 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). 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). Compared to the effect of the index composition on fund flows, the effect of index returns on fund flows is economically considerably larger.

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?

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

[18] 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.

one week. Table 6 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 week's index composition has no significant effect on this week's fund flows. 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 4. 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' members 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 an "all-winner-dummy" for days on which all members of an index trade at a gain and an "all-loser-dummy" for days on which all 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 7. 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 4.

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 8. 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 individuals' evaluation of 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 a portfolio's 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 care about and compare mental accounts across stocks when they evaluate their portfolios. How can these apparently inconsistent findings be reconciled? An important assumption underlying stock-by-stock accounting is that investors frame stock outcomes on the individual stock level. However, this does not need to imply that they also evaluate stocks narrowly. In essence, this clarifies an important assumption that might quickly be concluded from stock-by-stock accounting: Narrow framing of individual stock outcomes does not necessarily imply a completely isolated and detached evaluation of stocks in a portfolio. The question of how the level of outcome framing in a portfolio (how narrowly outcomes are framed) and the degree of evaluation of assets in a portfolio (how jointly assets are evaluated) interact across different investors and over time is one worthy of further study.

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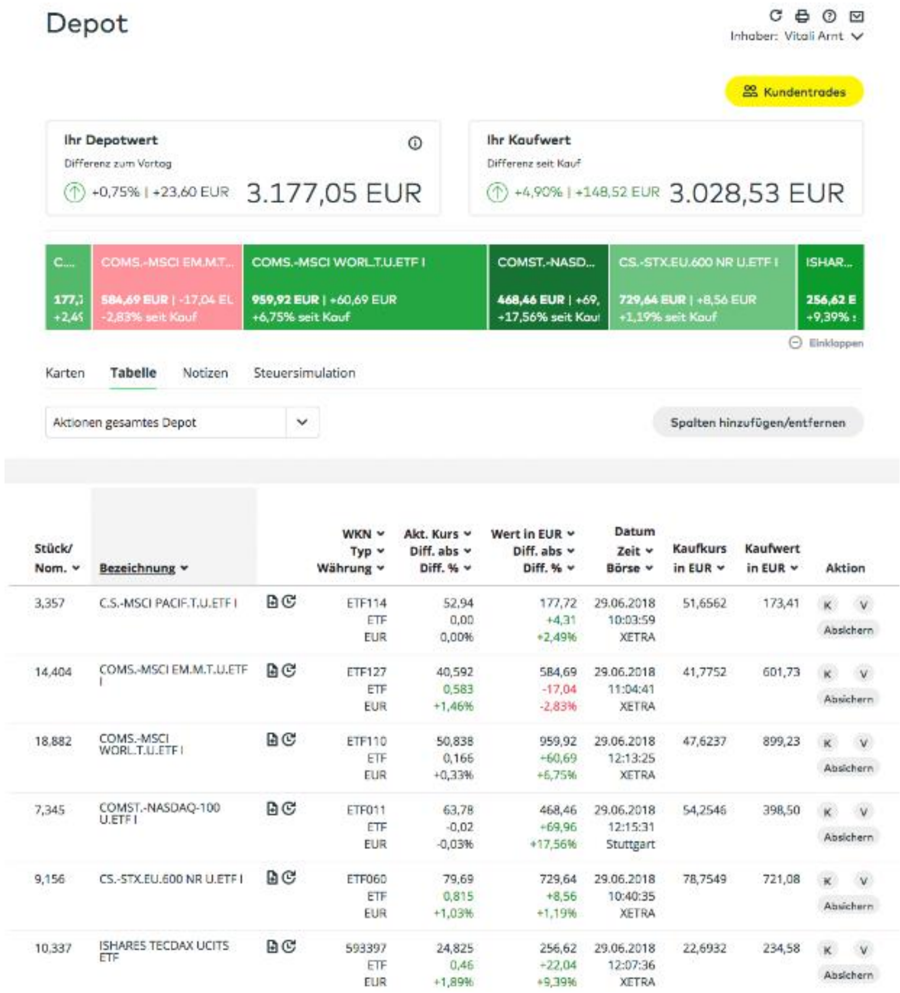
Figure 1: How Portfolio Performance Information Is Displayed

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)



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

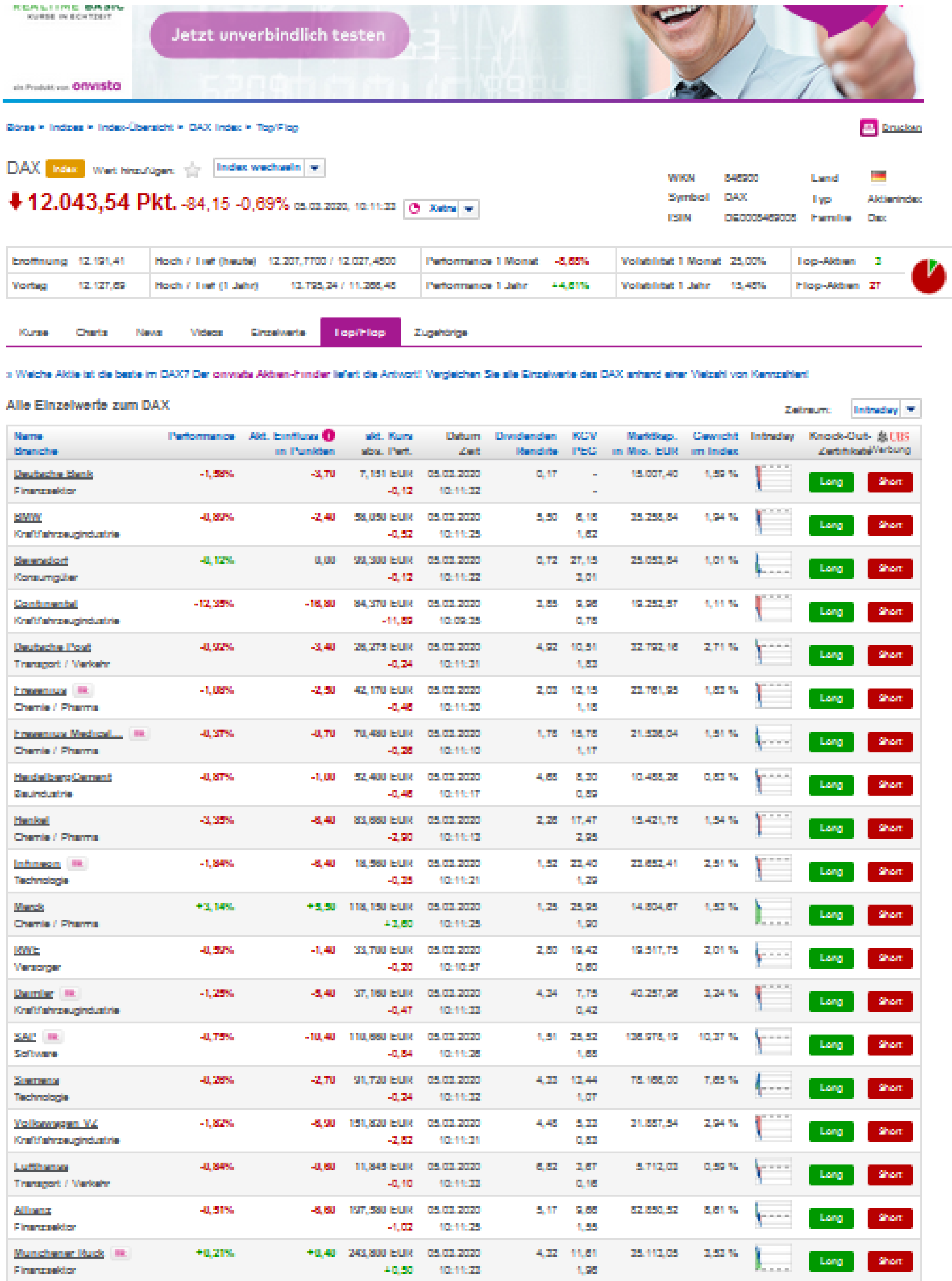


Figure 2: Portfolio Pair $G_pW_S - G_pL_S$ as presented in Experiment 1 and 2

This figure presents the portfolio pair $G_pW_S - G_pL_S$. On the left hand side, portfolio G_pW_S, labeled Portfolio X, and on the right hand side portfolio G_pL_S, labeled Portfolio Y, are demonstrated.

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 $G_pW_S - G_pL_S$. On the left hand side, portfolio G_pW_S, labeled Portfolio X, and on the right hand side portfolio G_pL_S, labeled Portfolio Y, are demonstrated. 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

Panel A shows participants' mean investments in US dollar in each portfolio for the two portfolio pairs $G_pW_S - G_pL_S$ and $L_pW_S - L_pL_S$, Panel B shows participants' mean satisfaction levels for each portfolio elicited on a Likert scale from 1: low to 7: high, Panel C shows participants' mean expected portfolio return estimates in US dollar, and Panel D shows participants' mean risk perception for each portfolio elicited on a Likert scale from 1: low risk to 7: high risk. The blue bars refer to Portfolio X which corresponds to the first two letters of each portfolio pair (e.g. GW for the first portfolio pair) and the red bars refer to Portfolio Y which corresponds to the second two letters of each portfolio pair (e.g. GL for the first portfolio pair). Displayed are 95%-confidence intervals.

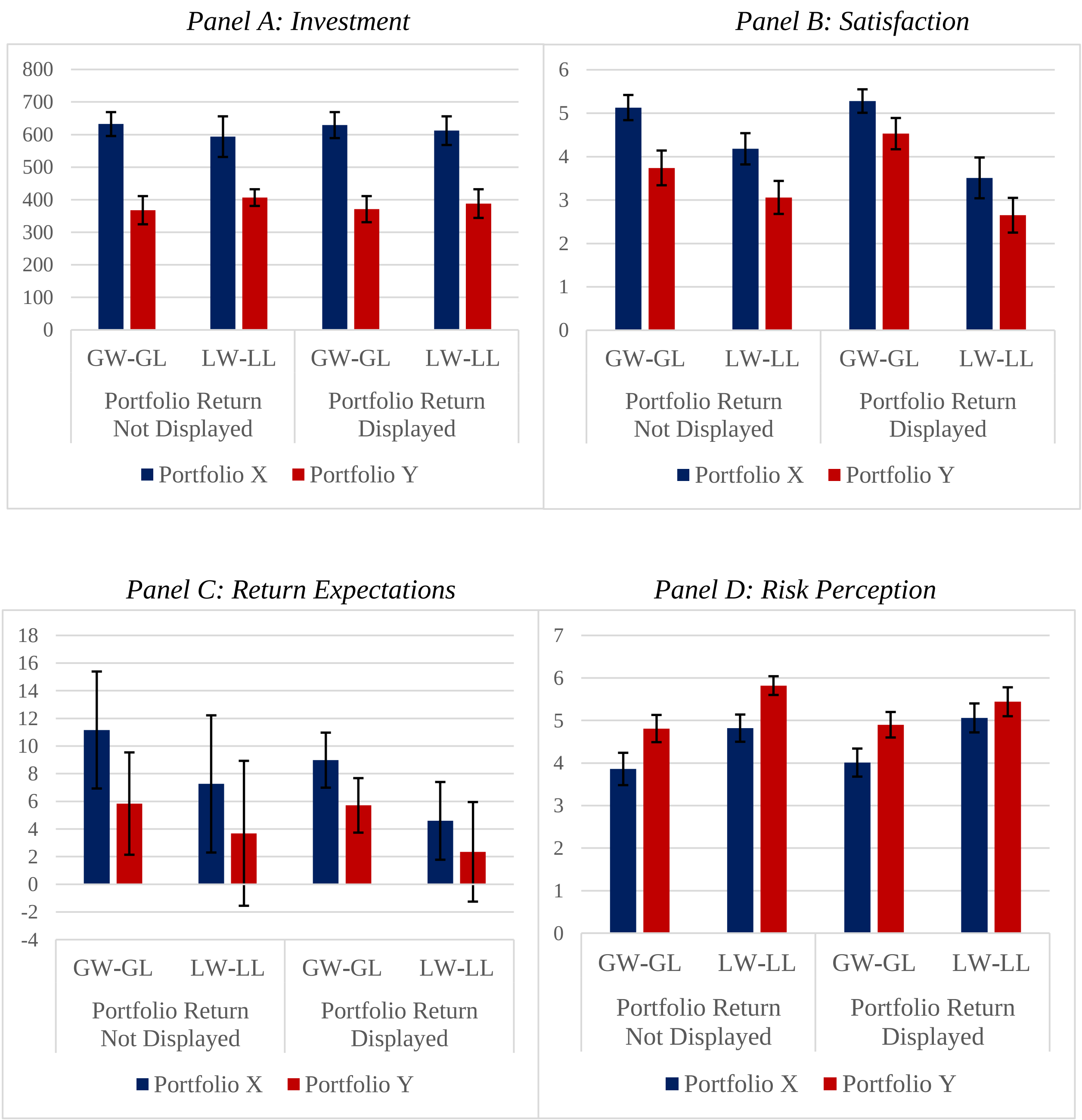
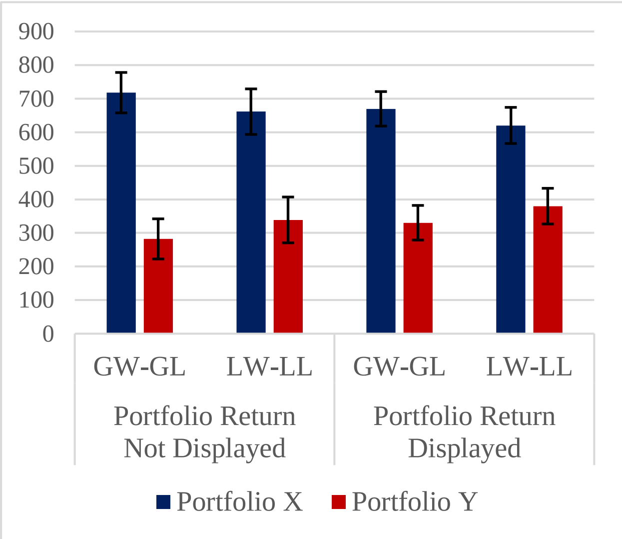


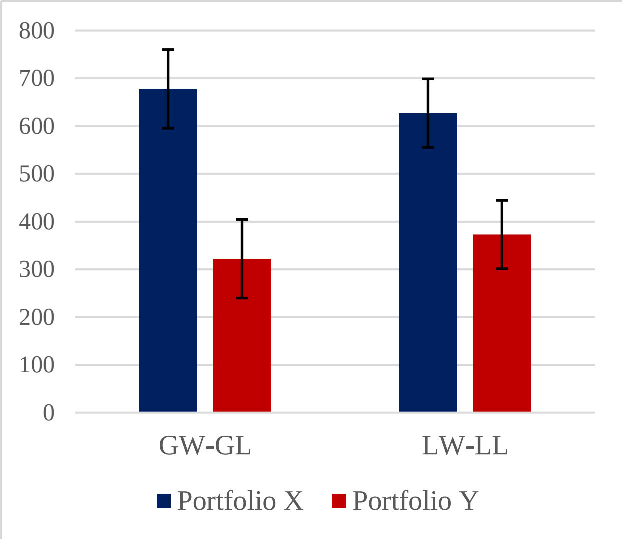
Figure 5: Baseline Treatments of Experiment 2

Panel A shows participants' mean investments in US dollar in each portfolio for the two portfolio pairs $G_pW_S - G_pL_S$ and $L_pW_S - L_pL_S$, Panel B shows participants' mean investments in US dollar in each portfolio for those participants who state the same expected returns for the two portfolios of a pair, and Panel C shows participants' mean risk perception for each portfolio elicited on a Likert scale from 1: low risk to 7: high risk. The blue bars refer to Portfolio X which corresponds to the first two letters of each portfolio pair (e.g. GW for the first portfolio pair) and the red bars refer to Portfolio Y which corresponds to the second two letters of each portfolio pair (e.g. GL for the first portfolio pair). Displayed are 95%-confidence intervals.

Panel A: Investment



Panel B: Investment Conditional on Expectations



Panel C: Risk Perception

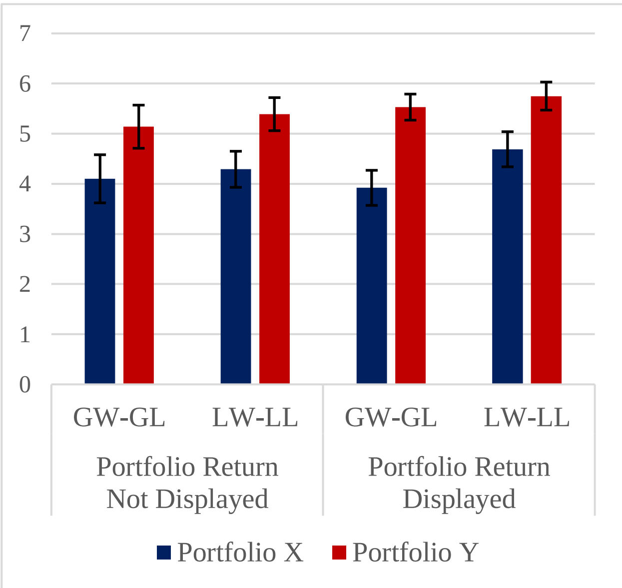
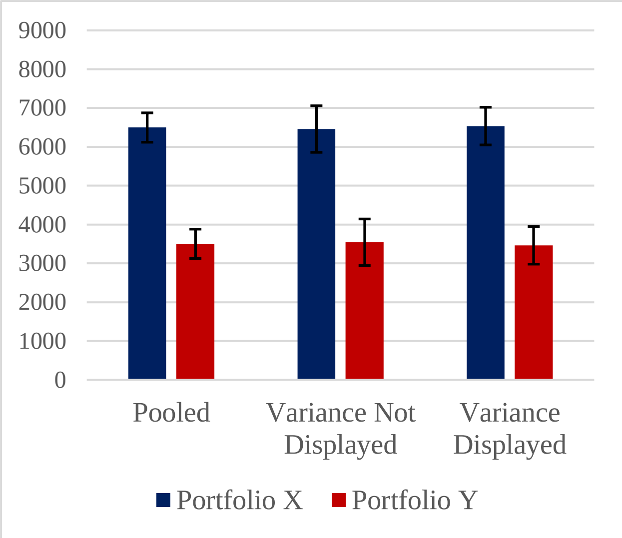


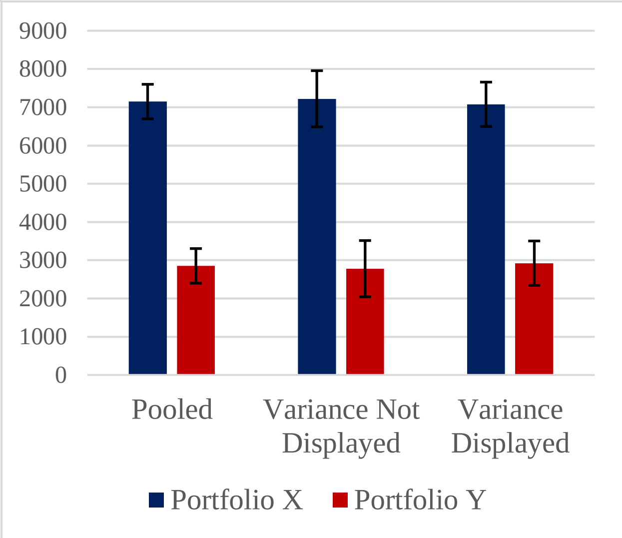
Figure 6: Baseline Treatment of Experiment 3

Panel A shows participants' mean investments in US dollar in each portfolio for the two portfolio pairs $G_pW_S - G_pL_S$ and $L_pW_S - L_pL_S$, Panel B shows participants' mean investments in US dollar in each portfolio for those participants who state the same expected returns for the two portfolios of a pair, Panel C shows participants' mean risk perception for each portfolio elicited on a Likert scale from 1: low risk to 7: high risk, and Panel D shows participants' mean risk perception for each portfolio for those participants who state the same expectations about returns and variance of returns. The blue bar refers to Portfolio X which corresponds to the first two letters of the portfolio pair (e.g. GW for the first portfolio pair) and the red bar refers to Portfolio Y which corresponds to the second two letters of the portfolio pair (e.g. GL for the first portfolio pair). Displayed are 95%-confidence intervals.

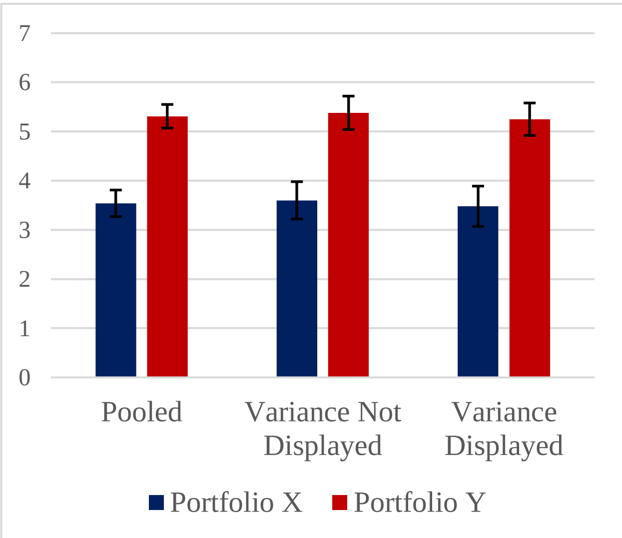
Panel A: Investment



Panel B: Investment Conditional on Expectations



Panel C: Risk Perception



Panel D: Risk Perception Conditional on Expectations

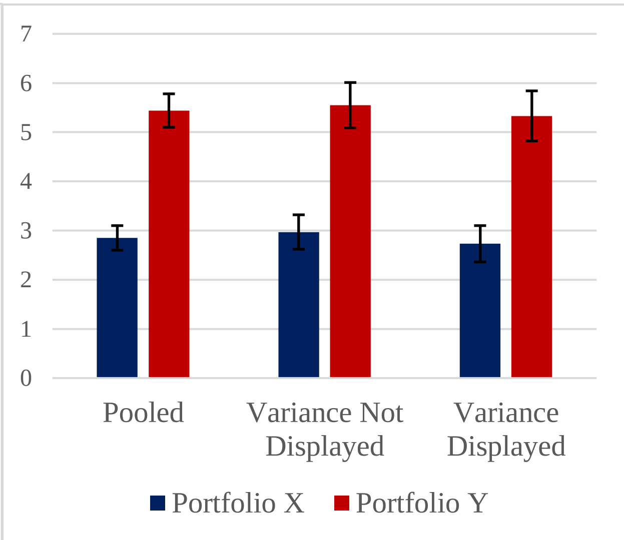
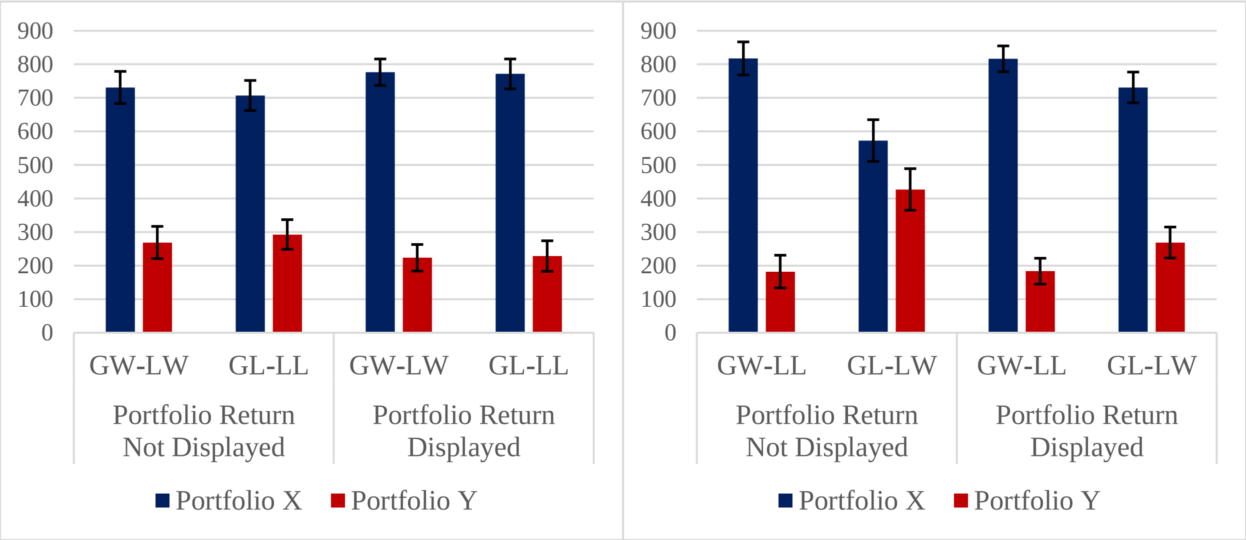


Figure 7: Additional Treatments of Experiment 1 and 2

The figure shows participants' mean investments in US dollar in each portfolio for the four portfolio pairs $G_pW_S - L_pW_S$, $G_pL_S - L_pL_S$, $G_pW_S - L_pL_S$ and $G_pL_S - L_pW_S$. Panel A reports the results for Experiment 1 and Panel B for Experiment 2. The blue bars refer to Portfolio X which corresponds to the first two letters of each portfolio pair (e.g. GL for the first portfolio pair) and the red bars refer to Portfolio Y which corresponds to the second two letters of each portfolio pair (e.g. LL for the first portfolio pair). Displayed are 95%-confidence intervals.

Panel A: Investment Experiment 1



Panel B: Investment Experiment 2

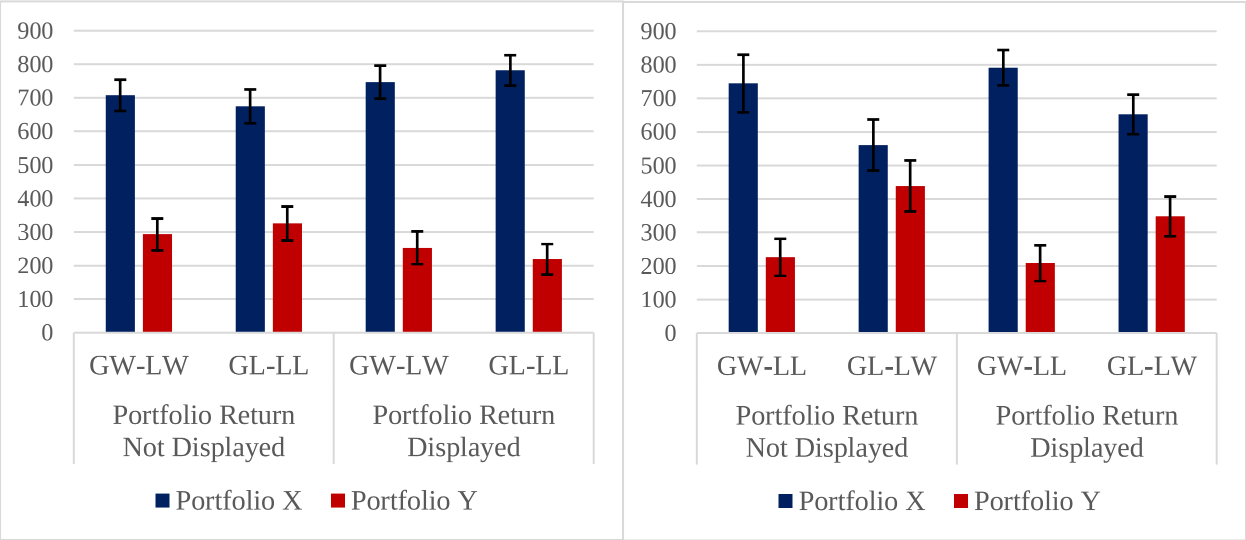


Table 1: Treatments in Experiment 1, 2, and 3

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 format 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, portfolio pair 1 in treatment 1 is denoted at $G_pW_S - G_pL_S$. 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. All treatments are run in experiment 1 and 2. In experiment 3 only treatment 1 portfolio pair 1 is run.

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	$G_pW_S - L_pL_S$	$G_pL_S - L_pW_S$

Table 2: 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 3: 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 4: 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 5: 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 6: 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 7: 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 8: 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.

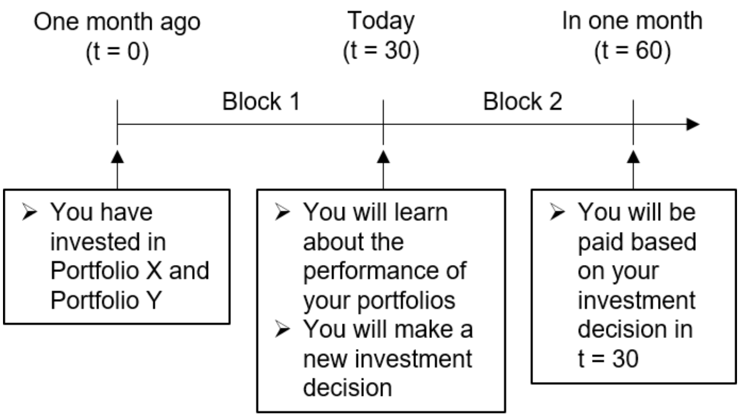
Experiment 3

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				

Comprehension Questions

Imagine, you observe the following performance of Stock A (+/- 4) in period 30: Number of positive return days = 18, number of negative return days = 12.

Please evaluate whether Stock A is more likely to be a good or a bad type.

- ◯ Good Type
- ◯ Bad Type

What is the expected return of Stock A (+/- 4) for the next period given the following performance in period 30: Number of positive return days = 18, number of negative return days = 12?

The computer will do the calculation in the investment task. However, we kindly ask you to do it on your own in this question such that you understand what the computer will do.

Hint: You need to use the formula 0.4*z for a good stock or -0.4*z for a bad stock.

- ◯ -2.0
- ◯ -1.6
- ◯ -1.2
- ◯ -0.8
- ◯ -0.4
- ◯ 0
- ◯ 0.4
- ◯ 0.8
- ◯ 1.2
- ◯ 1.6
- ◯ 2.0

Please evaluate the statement: Stock A (+/- 4) can only make a return of +4 or -4 per period.

- ◯ True
- ◯ False

Part B: Screenshots of the Experiments

Experiment 1

Figure B-I: Screen with Satisfaction Question

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

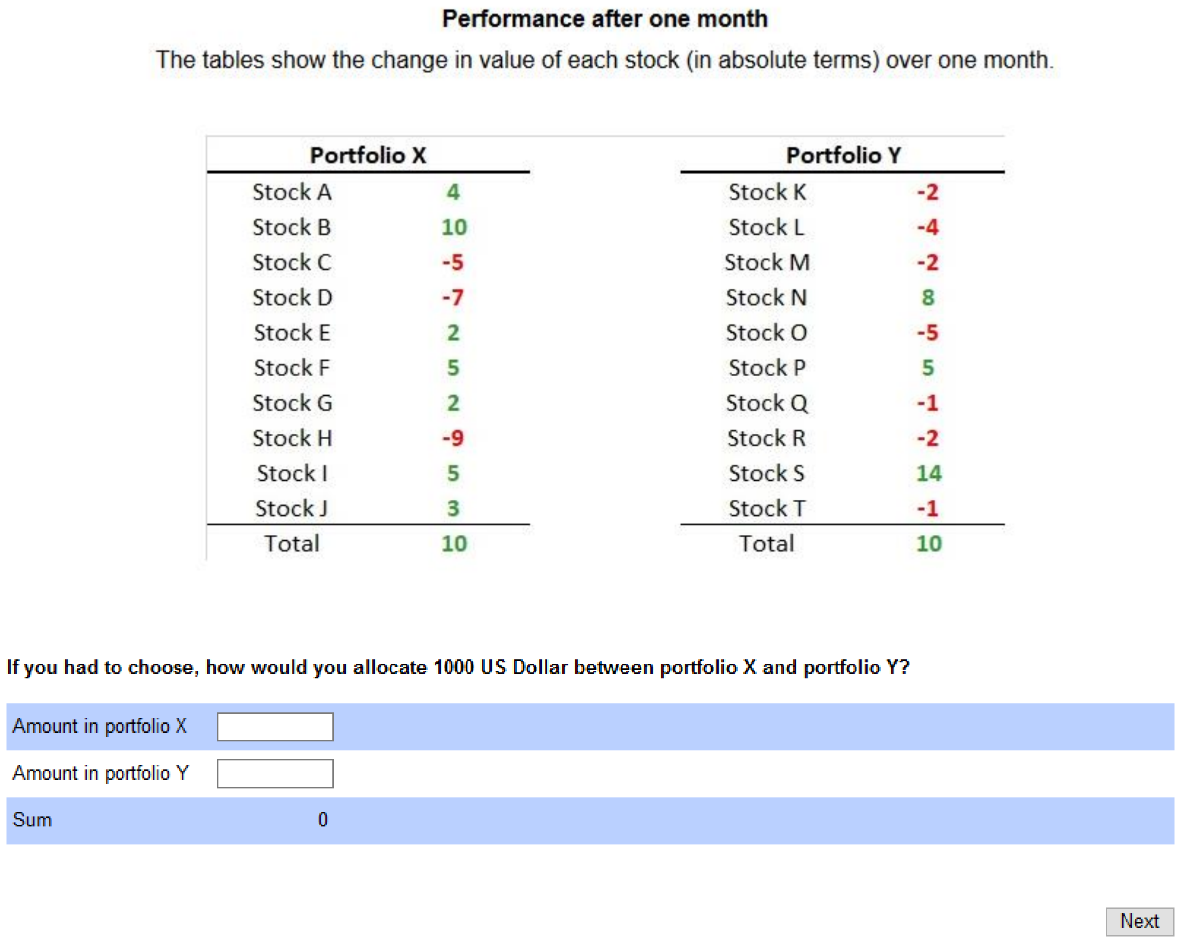
Portfolio Y	
Stock K	-2
Stock L	-4
Stock M	-2
Stock N	8
Stock O	-5
Stock P	5
Stock Q	-1
Stock R	-2
Stock S	14
Stock T	-1
Total	10

How satisfied are you with the past performance of your portfolios?

	1 very unsatisfied	2	3	4	5	6	7 very satisfied
Portfolio X	○	○	○	○	○	○	○
Portfolio Y	○	○	○	○	○	○	○

Next

Figure B-II: 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

Figure B-III: Screen with Return Expectations and Risk Perception Question

Performance after one month

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

Portfolio X		Portfolio Y	
Stock A	4	Stock K	-2
Stock B	10	Stock L	-4
Stock C	-5	Stock M	-2
Stock D	-7	Stock N	8
Stock E	2	Stock O	-5
Stock F	5	Stock P	5
Stock G	2	Stock Q	-1
Stock H	-9	Stock R	-2
Stock I	5	Stock S	14
Stock J	3	Stock T	-1
Total	10	Total	10

Let us ask you about your risk and return expectations.

By how much will the value of portfolio X/portfolio Y increase/decrease (in US Dollar) in the next month?

Please use a minus sign to indicate a decrease in value.

The value of portfolio X will increase/decrease by

The value of portfolio Y will increase/decrease by

On a scale from 1 (not risky at all) to 7 (very risky) how risky do you perceive portfolio X/portfolio Y?

	1 not risky at all	2	3	4	5	6	7 very risky
Portfolio X	○	○	○	○	○	○	○
Portfolio Y	○	○	○	○	○	○	○

Next

Experiment 3

Figure B-IV: 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-V: Screen with Return Expectations and Volatility

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

Your evaluation of good and bad stocks:

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

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

The expected return of Portfolio X for the next period: **4**
The expected standard deviation of Portfolio X for the next period: **24.3**

The expected return of Portfolio Y for the next period: **4**
The expected standard deviation of Portfolio Y for the next period: **24.3**

Figure B-VI: Screen with Risk Perception Question

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

On a scale from 1 (not risky at all) to 7 (very risky) how risky do you perceive Portfolio X/Portfolio Y?

	1 not risky at all	2	3	4	5	6	7 very risky
Portfolio X	○	○	○	○	○	○	○
Portfolio Y	○	○	○	○	○	○	○

Figure B-VII: 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.

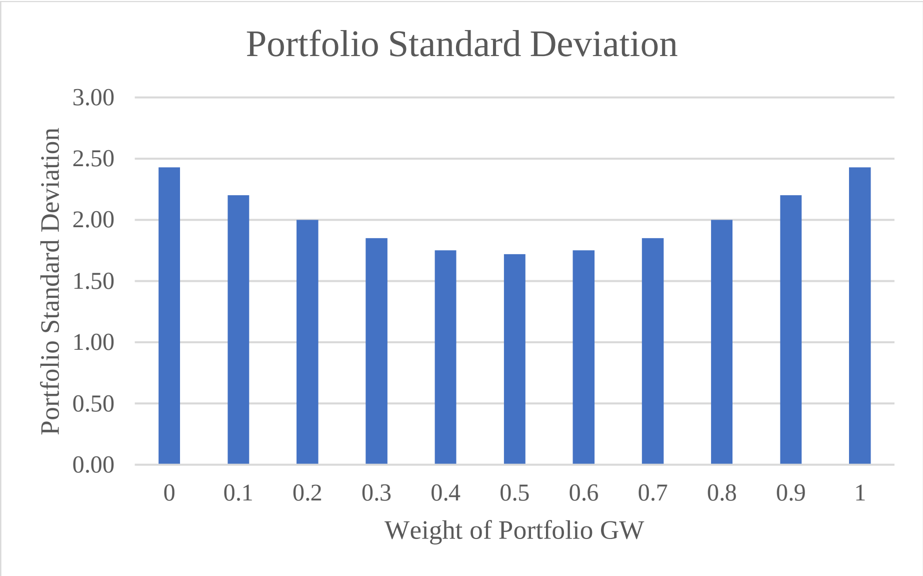
Table C-I: Portfolio Expected Return and Standard Deviation

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)

The figure shows participants' mean satisfaction levels for each portfolio elicited on a Likert scale from 1: low to 7: 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). In each panel, the left part of the figure displays mean investments for those treatments in which the total portfolio return was not displayed during the experiment and the right part describes mean investments for those treatments in which the total portfolio return was displayed during the experiment. The blue bars refer to Portfolio X which corresponds to the first two letters of each portfolio pair (e.g. GL for the first portfolio pair) and the red bars refer to Portfolio Y which corresponds to the second two letters of each portfolio pair (e.g. LL for the first portfolio pair). Displayed are 95%-confidence intervals.

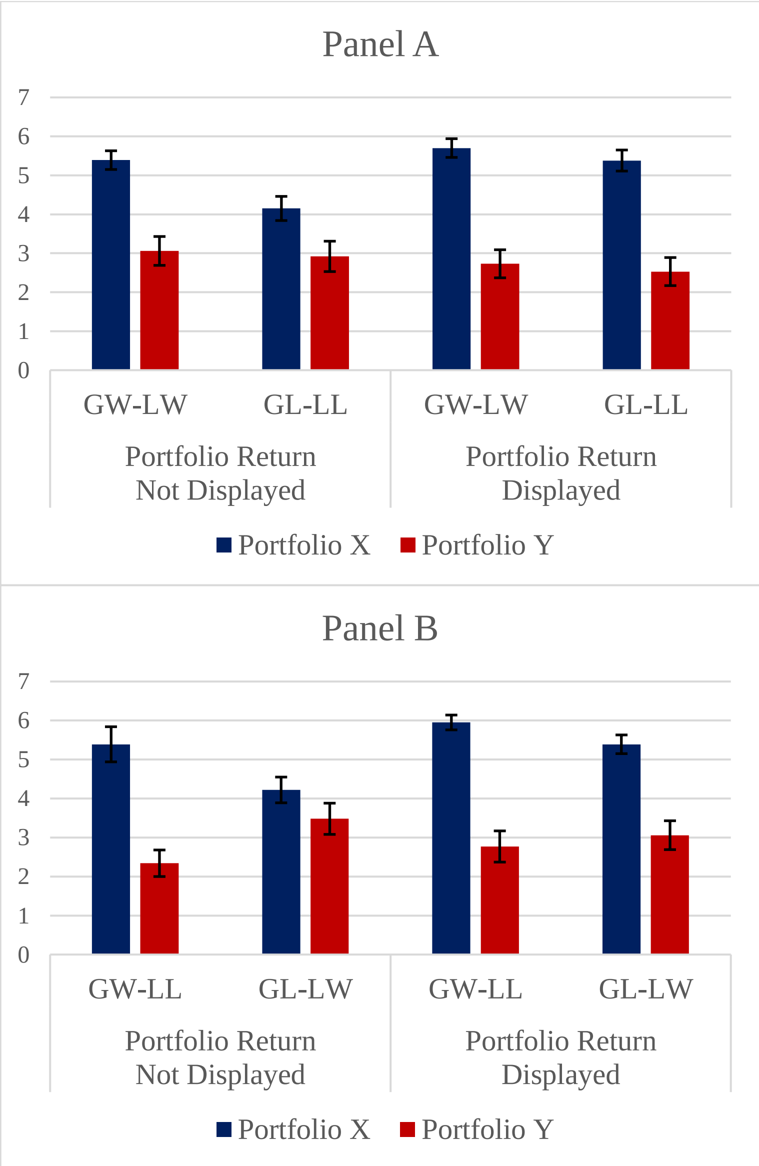


Figure D-II: Return Expectations in Experiment 1 (Additional Treatments)

The figure shows participants' mean expected returns for each portfolio elicited on a Likert scale from 1: low to 7: 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). In each panel, the left part of the figure displays mean expected returns for those treatments in which the total portfolio return was not displayed during the experiment and the right part describes mean expected returns for those treatments in which the total portfolio return was displayed during the experiment. The blue bars refer to Portfolio X which corresponds to the first two letters of each portfolio pair (e.g. GL for the first portfolio pair) and the red bars refer to Portfolio Y which corresponds to the second two letters of each portfolio pair (e.g. LL for the first portfolio pair). Displayed are 95%-confidence intervals.

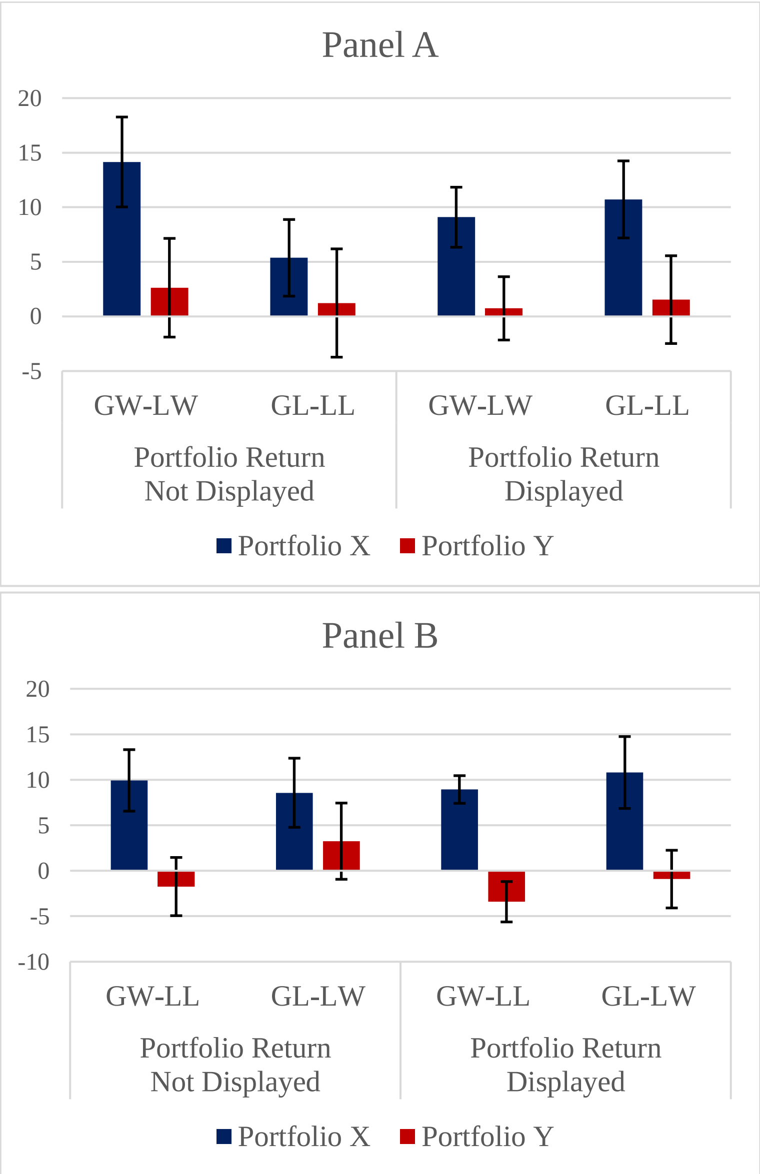
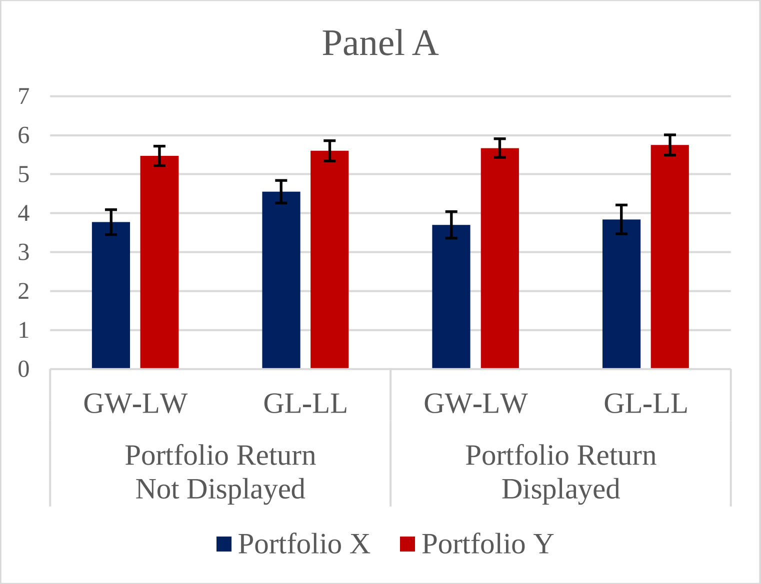


Figure D-III: Risk Perception in Experiment 1 (Additional Treatments)

The figure shows participants' mean risk perception for each portfolio elicited on a Likert scale from 1: low to 7: 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). In each panel, the left part of the figure displays mean risk perception for those treatments in which the total portfolio return was not displayed during the experiment and the right part describes mean risk perception for those treatments in which the total portfolio return was displayed during the experiment. The blue bars refer to Portfolio X which corresponds to the first two letters of each portfolio pair (e.g. GL for the first portfolio pair) and the red bars refer to Portfolio Y which corresponds to the second two letters of each portfolio pair (e.g. LL for the first portfolio pair). Displayed are 95%-confidence intervals.



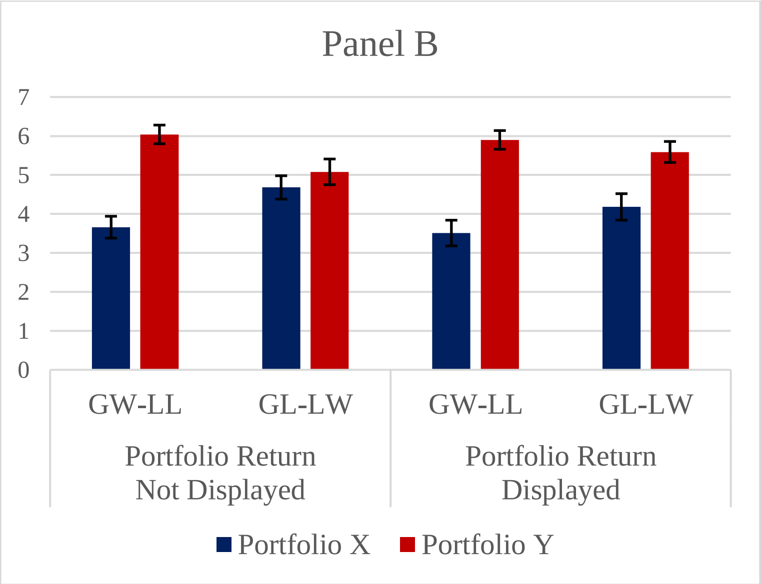


Figure D-IV: Investment in Experiment 2 Conditional on Return Expectations (Additional Treatments)

The figure shows participants' mean investments in US dollar in each portfolio of those participants who state the same expected returns for the two portfolios of a pair. The portfolio pairs are $G_pW_S - L_pW_S$ 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 Portfolio X which corresponds to the first two letters of each portfolio pair (e.g. GW for the first portfolio pair) and the red bars refer to Portfolio Y which corresponds to the second two letters of each portfolio pair (e.g. LW for the first portfolio pair). Displayed are 95%-confidence intervals.

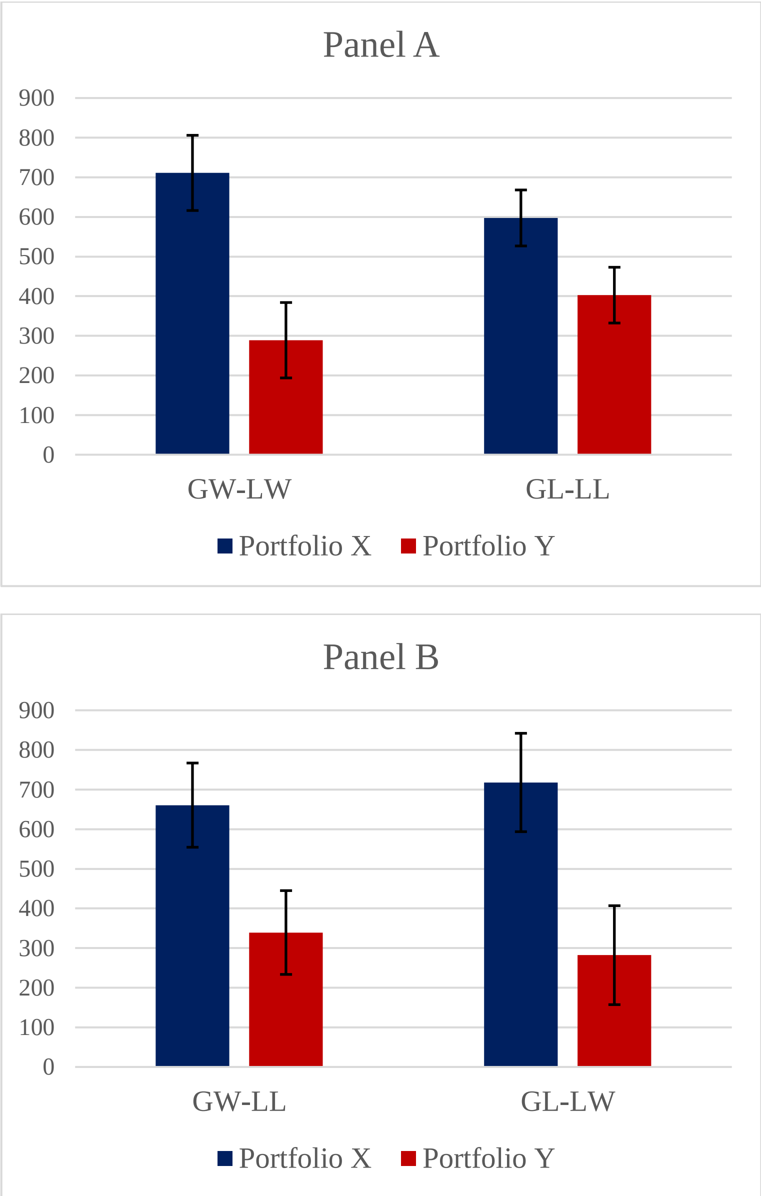
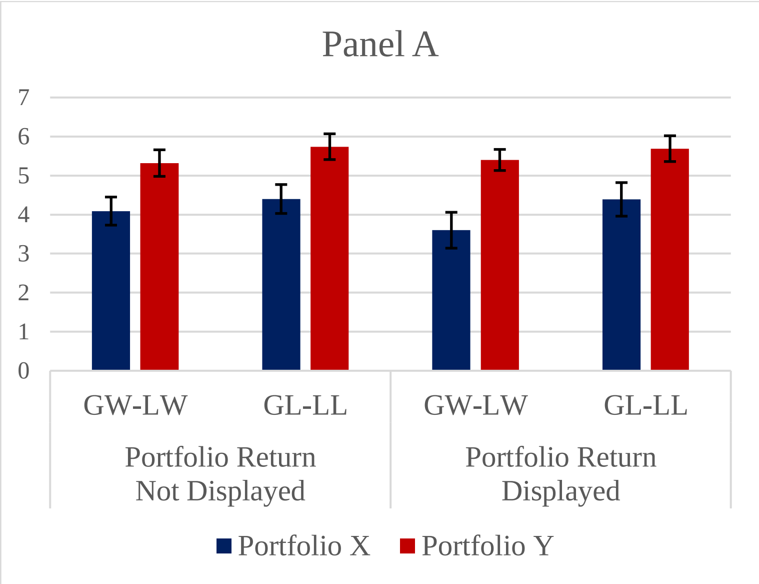


Figure D-V: Risk Perception in Experiment 2 (Additional Treatments)

The figure shows participants' mean risk perception for each portfolio elicited on a Likert scale from 1: low to 7: 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). In each panel, the left part of the figure displays mean risk perception for those treatments in which the total portfolio return was not displayed during the experiment and the right part describes mean risk perception for those treatments in which the total portfolio return was displayed during the experiment. The blue bars refer to Portfolio X which corresponds to the first two letters of each portfolio pair (e.g. GL for the first portfolio pair) and the red bars refer to Portfolio Y which corresponds to the second two letters of each portfolio pair (e.g. LL for the first portfolio pair). Displayed are 95%-confidence intervals.



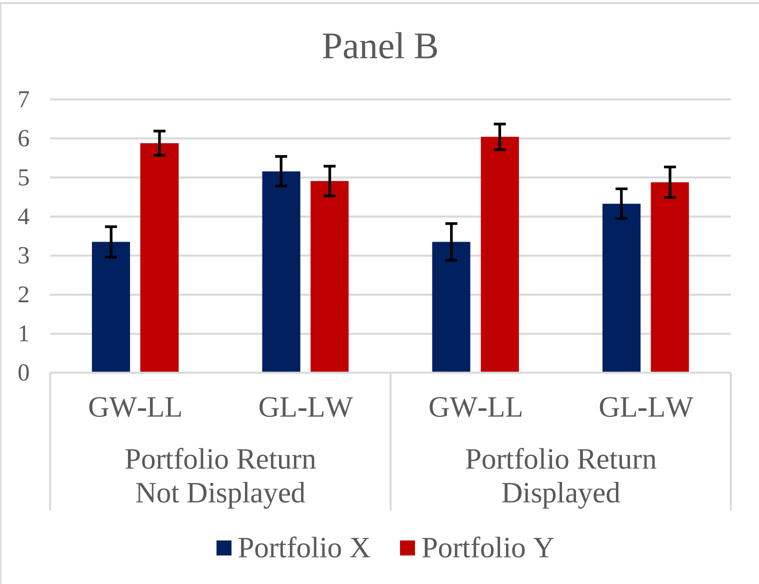


Figure D-VI: Relation between Portfolio Composition Measure and Index Return

The figure shows the relation between the fraction of winners in an index and the index return for the sample of four leading equity market indices. For illustrative purposes, we limit the index returns between -6% and 6%.

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 (1)	Total value displayed (2)	Total value not displayed (3)	Entire sample (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