The Perception of Dependence, Investment Decisions, and Stock Prices[a]

Michael Ungeheuer and Martin Weber[b]

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Abstract

How do investors perceive dependence between stock returns? And how does their perception of dependence affect investments and stock prices? We show experimentally that investors understand differences in dependence, but not in terms of correlation. Subjects rather assess the frequency of comovement by applying a simple counting heuristic. Consequently, they diversify more when the frequency of comovement is lower even if correlation is higher. Building on our experimental findings, we conduct an empirical analysis of 1963-2015 US stock returns revealing a robust return premium for stocks with high frequencies of comovement with the market return.

Keywords: Biased Beliefs, Dependence, Investment Decisions, Correlation Neglect, Diversification, Asset Pricing

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[b] Michael Ungeheuer (corresponding author): Chair of International Finance at the University of Mannheim, Address: L9, 1-2, 68131 Mannheim, Germany, Telephone: +49-621-181-1640, E-mail: michael.ungeheuer@gess.uni-mannheim.de. Martin Weber: Chair of Finance and Banking at the University of Mannheim, Address: L5, 2, 68131 Mannheim, Germany, Telephone: +49-621-181-1532, E-mail: weber@bank.BWL.uni-mannheim.de and the Centre for Economic Policy Research, London EC1V 3PZ, United Kingdom.

1 Introduction

We study the formation of beliefs about dependence between stock returns, as well as the impact of dependence on investment decisions and stock prices. In several laboratory experiments, we show that subjects are able to understand dependence between frequent, moderate returns. However, in spite of spending more time viewing infrequent, extreme returns, they are not able to correctly answer questions about dependence in these states. Hence, their overall beliefs about dependence are driven by the frequency of comovement between asset returns, not correlation. Consistent with their beliefs about dependence being driven by a counting heuristic, subjects diversify more when the frequency of comovement between asset returns decreases, even if correlation increases due to strong positive dependence in extreme returns. We apply our insights from the laboratory to 1963-2015 US stock returns, and find that stocks with higher frequencies of comovement exhibit a robust return premium. This is consistent with investors requiring a reward for holding stocks with high perceived dependence. In contrast β, the measure of dependence derived from normative portfolio theory (Markowitz (1952)) is not priced in the cross-section of stock returns (Fama and French (2004)).

In many economic decisions, dependence between different sources of risk plays an important role. Particularly in finance, the impact of dependence on portfolio selection has been a focal topic since Markowitz (1952). As an illustration, investors need to decide how much of their savings to put into asset classes, such as stocks, bonds, and real estate. Empirically, the returns of these asset classes are dependent amongst each other. Investing into asset classes that increase in value when other asset classes decrease in value (negative dependence) reduces overall portfolio risk. As Markowitz, economists have mainly used Pearson correlation as the relevant measure of dependence in these diversification decisions. Asset classes, which have low correlation with a portfolio provide an insurance for unexpectedly low or high portfolio returns and thus decrease portfolio return variance. Hence, they should have a high weight in optimal portfolios. Building on Markowitz (1952), Sharpe (1964) shows that in equilibrium, the high diversification benefits of assets with low dependence on market returns (or low β) should lead to higher prices and lower expected returns. However, the behavioral finance literature shows that correlation is a concept, which is hard to grasp for many investors. Starting with Kroll, Levy, and Rapoport (1988), experiments suggest that investors neglect correlation altogether. And historical stock returns provide little evidence of β being priced (Fama and French (2004)). One reason for these findings may be that investors perceive dependence not as correlation or β, but differently. For instance, they might use a simple counting heuristic and thus understand the frequency of comovement between asset returns, i.e. the frequency of equally signed asset returns. Or their beliefs might be driven by salient, extreme returns. Additionally, even with rational expectations about dependence, investors might care more about dependence in certain states—e.g. when it increases the risk of large losses (see Roy (1952))—so that correlation is not the relevant measure of dependence. The experimental literature on portfolio selection up to this study does not provide an answer to the questions: How do investors perceive dependence, and how does this influence their investment decisions? We fill this knowledge gap and then link our experimental insights to historical stock returns.

We run four laboratory experiments to analyze how varying dependence between asset returns influences beliefs about dependence and investment decisions. We vary the dependence between two assets' returns across treatments, keeping marginal distributions (return means, volatilities etc.) constant. We then ask participants to invest their endowment into the two assets and elicit their beliefs about dependence. In our first experiment, we vary linear dependence.[1] We find that participants' beliefs are consistent with changes in dependence. Consequently, participants diversify less when dependence increases, in line with Markowitz (1952). In our next experiments, we vary non-linear dependence, decreasing dependence in frequent, moderate returns while increasing dependence in infrequent, extreme returns. We find that participants' beliefs are driven by dependence in frequent, moderate returns, consistent with a counting heuristic. Participants do not understand dependence in infrequent, extreme returns and diversify less when dependence increases in frequent, moderate returns, even if correlation decreases due to decreasing dependence in infrequent, extreme returns. Thus their behavior is exactly opposite to what one would expect according to Markowitz (1952). In summary, while differences in dependence are taken into account by participants, beliefs and choices are not explained by correlation, but by a simple counting heuristic.

Based on this insight, we turn to historical stock returns and test whether actually per-

[1] We use the term 'linear dependence' when the expected value of one asset's return is linear in the other asset's return, i.e. $E(r_1|r_2) = a + b \cdot r_2$. If this relation does not hold, we denote the dependence between two assets as 'non-linear'.

ceived dependence is priced. If enough investors' beliefs about dependence and investment decisions are driven by dependence in frequent returns instead of correlation, this could lead to a return premium for stocks with higher frequencies of comovement with the market. We test this hypothesis using 1963-2015 US stock returns and find strong evidence of a return premium for stocks that frequently have the same sign in stock return as the S&P 500. In particular during the second half of our sample (1989-2015), when attention towards portfolio and risk management became stronger, we find a strong return premium of 5.53% per year (Carhart-alpha 6.08%, Sharpe Ratio 0.65, with momentum's Sharpe Ratio at 0.46 during the same time period) for high-minus-low quintile stock returns, when sorting by frequency of comovement. This premium is not explained by a large number of factor models. In Fama and MacBeth (1973) regressions we show that neither other measures of dependence like downside risk, nor measures of idiosyncratic risk like idiosyncratic volatility or maximum daily returns can explain our finding. The high returns of stocks with frequent comovement with the market are robust to controlling for liquidity, trading activity, the Fama and French (2015) factors, industry- and size-decile-fixed effects. Hence, while there is little evidence of linear measures of dependence like β being priced (Fama and French (2004)), we find a robust return premium for a measure of dependence motivated by experimental evidence on the perception of dependence. The frequency of return comovement matters, not only on the level of individual portfolio selection decisions in the laboratory, but also for historical aggregate market prices.

We contribute to the experimental literature in several ways. First, we ask a new research question: In addition to analyzing the impact of linear dependence on investors' beliefs and choices, we analyze the impact of dependence in frequent, moderate versus infrequent, extreme returns, i.e. we analyze variation in non-linear dependence. Earlier studies on the impact of dependence on portfolio selection focus on varying linear dependence. In contrast, we analyze the impact of dependence *in general*, including non-linear dependence. As an illustration, we display the conditional expectations for our treatments in experiments 1 and 2 in Figure 1. Treatments in experiment 1 exhibit linear dependence: The expectations for the return of one stock given the return of the other stock are located on the line $E(r_2|r_1) = 4\% + \rho \cdot r_1$, where ρ is the correlation between stock 1's return r_1 and stock 2's return r_2. E.g., for treatment 1 (3) correlation is negative (positive) at -0.6 (+0.6), so that $E(r_2|r_1) = 4\% - 0.6 \cdot r_1$ ($E(r_2|r_1) = 4\% + 0.6 \cdot r_1$). In contrast, the treatments in experiment 2 exhibit non-linear dependence: In particular, dependence in frequent, moderate returns is opposite to dependence in infrequent, extreme returns. Although there is strong variation in dependence between the two treatments of experiment 2, correlation is zero in both treatments. Thus correlation does not capture these changes in non-linear dependence. To the best of our knowledge we are the first to experimentally test the perception of non-linear dependence and its impact on investment decisions.

[INSERT FIGURE 1 ABOUT HERE]

Second, we communicate dependence via sampling of graphical information (price paths) and numerical information (returns colored in green if positive and red if negative), instead of relying on unrealistic direct statements about probabilities of joint events.[2] We avoid confounding effects of changes in volatility across treatments by keeping marginal distributions constant. An early experimental test of the impact of correlation on portfolio selection is Kroll, Levy, and Rapoport (1988). They find that investors neglect information on correlations in their portfolio decisions. Information is communicated via stating means, standard-deviations and correlations of jointly normally distributed returns with varying levels of correlation across treatments. In more current research, Kallir and Sonsino (2009) and Eyster and Weizsäcker (2011) also provide evidence in line with correlation neglect. Kallir and Sonsino (2009) vary the dependence for 2×2 equally probable states (2-assets with 2 possible returns each) and communicate riskiness via probability statements as Kroll, Levy, and Rapoport (1988). In contrast to these two studies, Eyster and Weizsäcker (2011) do not vary the decision problem, but vary the framing of decisions by letting participants invest into two assets 1 and 2 in the first treatment and into assets 1 and 2' – where 2' is a linear combination of assets 1 and 2 – in the second treatment. This keeps the decision problem the same, while changing linear dependence and marginal distributions. Eyster and Weizsäcker (2011) also directly state the probabilities for all states.[3] Hence, we contribute to the litera-

[2]Laudenbach, Ungeheuer, and Weber (2016) analyze the effect of different presentation formats on the perception of dependence and investment decisions. They show that correlation neglect—the most common finding from the experimental literature—disappears when participants sample return observations (a relatively realistic presentation format) instead of viewing probability statements about joint events (an unrealistic presentation format).

[3]This is not supposed to be an exhaustive literature review, but rather a representative sample of the literature. Other studies on the impact of correlation on investment decisions include Kroll and Levy (1992), Benartzi and Thaler (2001), Hedesström, Svedsäter, and Gärling (2006), Klos and Weber (2006)

ture by strictly keeping marginal distributions constant and by presenting information more realistically.

Third, our study contributes to the literature on rare events. Whether investors focus on or neglect rare, extreme events becomes relevant when non-linear dependence is varied. Results in the literature are strongly dependent on the way risky choices are communicated. On the one hand, previous experiments find overweighting of rare observations when the probabilities of these events are communicated via description, i.e. when probabilities for events are directly stated. This motivates the probability weighting function in the context of prospect theory, see Kahneman and Tversky (1979) and Tversky and Kahneman (1992). Based on these results, one could hypothesize that investors focus on dependence in salient extreme events. On the other hand, as shown by Hertwig, Barron, Weber, and Erev (2004), Abdellaoui, L'Haridon, and Paraschiv (2011), and Kaufmann, Weber, and Haisley (2013), experience sampling (the sequential drawing of potential outcomes) can lead to reduced overweighting or even underweighting of small probability events. Payzan-LeNestour (2015) finds that participants—even after being told about the underlying distribution—repeatedly agree to a bet with frequent positive outcomes, but extreme negative skewness and a negative expected value ('picking up pennies in front of a steamroller'). Based on these results, one could hypothesize that investors use a counting heuristic and focus on dependence in frequent events. We directly test these competing hypotheses by separately varying dependence in extreme (but rare) and frequent (but moderate) observations.

Fourth, a difference between the previous literature on correlation neglect and our experiments is our focus on beliefs about dependence. We directly ask for participants' expectations about dependence in the domains of extreme and moderate returns, and thus differentiate between biased beliefs about dependence and over- or underweighting of observations in preferences. Barberis (2013) discusses the importance of disentangling biased beliefs and certain preferences with respect to rare tail events. As an illustration, the probability weighting in prospect theory is part of the preferences. Given objective beliefs about rare events' probabilities, the prospect theory decision maker still overweights rare events. Relative to such preference-based overweighting, biased beliefs about the probability of rare (joint) events have very different implications for policy makers: It is obvious that biased beliefs are irra-

Gubaydullina and Spiwoks (2009), Cornil and Bart (2013), Merkle (2016) and Reinholtz, Fernbach, and de Langhe (2016).

tional and 'de-biasing' agents should improve decisions, whereas the irrationality of a utility function with probability weighting is not that clear-cut.

Last, we contribute to the literature on empirical asset pricing by testing whether the counting heuristic we find in the laboratory can explain the historical cross-section of stock returns. Although there is little evidence for the Sharpe (1964) CAPM-β being priced (Fama and French (2004)), mounting evidence suggests that dependence during down markets[4] or market crashes[5] is priced. We do not provide an explanation for the historical return premium for crash risk, since our participants in the lab neglect dependence in extreme, rare returns, instead of particularly focusing on crashes. Conversely, our empirical asset pricing analysis is motivated by our experimental evidence on biased beliefs about dependence, i.e. we go from the laboratory to historical return data. The novel return premium we measure for stocks with a high frequency of comovement with market returns is well motivated by experiments and distinct from downside risk premiums.

The remainder of the paper is structured as follows: In Section 2 we show experimentally, that a simple counting heuristic drives the perception of dependence and investment decisions. Particularly, in Subsection 2.1 we describe the main features of our experimental design. We then report the results from an experiment where we vary linear dependence in Subsection 2.2. In a second experiment, described in Subsection 2.3, we keep correlation constant (at zero) and vary non-linear dependence, i.e. dependence in extreme vs. moderate returns. In Subsection 2.4, we describe results from a third experiment on non-linear dependence, where we increase dependence in frequent, moderate returns, while decreasing correlation. In a fourth experiment, we analyze how our results are influenced by the way we display information, see Subsection 2.5. In Section 3 we take our insights from experiments to historical stock returns and show that perceived dependence (the frequency of return comovement) is priced. Finally, we conclude in Section 4.

[4]Motivated by Gul (1991)'s disappointment aversion utility, Ang, Chen, and Xing (2006) find a premium for downside-β, i.e. β conditional on negative market returns.

[5]Chabi-Yo, Ruenzi, and Weigert (2015), Weigert (2016), and Ruenzi, Ungeheuer, and Weigert (2016).

2 Experimental Evidence

We experimentally test the following hypotheses on the effects of changes in linear dependence (H_{11} and H_{12}) and non-linear dependence (H_{21} and H_{22}):

H_{11}: Investors are able to perceive changes in linear dependence (Beliefs).

H_{12}: Investors diversify more when linear dependence decreases (Choice).

H_{21}: Investors are able to perceive changes in non-linear dependence. (Beliefs).

H_{22}: Investors diversify more when perceived overall dependence decreases (Choice).

2.1 Experimental Setup

To determine how investment decisions (choices) and the perception of dependence (beliefs) are influenced by actual dependence, we conduct several experiments. In experiment 1 we start with the relatively simple hypotheses H_{11} and H_{12} and test them by varying linear dependence. Varying linear dependence lets us compare our results to previous research, where the most common finding is 'correlation neglect'. In experiments 2, 3 and 4 we test hypotheses H_{21} and H_{22} by varying dependence in infrequent, extreme versus frequent, moderate returns. In all experiments participants are asked to make portfolio selection decisions and to state their beliefs in situations with varying dependence between two stocks. We choose an allocation decision with only two stocks and no risk-free asset to keep the investment decision as simple as possible. There are several challenges that have to be met by the design of experiments on portfolio selection.

First, directly displaying probabilities for different states–although common in experiments that find correlation neglect–is unrealistic. Hence, we let participants see price paths (graphical display) and returns (numerical display) to communicate the risky choice they face. In experiment 4 (Section 2.5) we test the effects of the presentation mode by showing half of participants price paths only, and the other half returns only. As is often done with real market data, returns are colored green if positive, and red if negative. Each participant gets to see a representative sample from the treatment's return distribution. Rare, extreme events have a probability of only 5% in all experiments, so that we need to show each participant 100 observations for a representative sample. Since exponential growth makes it very hard to discern returns at the beginning of a 100-year sample, we instead show 10×10-year subsamples, which participants click through.[6]

Second, effects due to varying marginal distributions (e.g. volatilities) of each asset could drive the results. This problem is solved via using the same marginal distributions across treatments. Consequently means, standard-deviations and all other moments are equal across treatments. All that varies across the different decision situations is dependence. This approach is inspired by the concept of copula functions, which isolate structures of dependence between random variables from marginal distributions. Thus any measured effect between treatments must be a result of the varied dependence.

Third, it is likely that the order of observations each participant observes has a systematic influence on the participants' investment decisions. Asparouhova, Lemmon, and Hertzel (2009) for instance show that participants expect reversals (continuation) after short (long) streaks when shown sequences of randomly generated *independent* numbers. Cohn, Engelmann, Fehr, and Maréchal (2015) find that risk aversion increases after participants are primed with bust scenarios. Mussweiler and Schneller (2003) report that extremely high (low) observations on price paths lead to a higher likelihood of purchases (sales). Using the same price path for all participants by treatment—even if it is a representative sample of the treatment's distribution—could thus lead to dependence of participants' answers on a feature of the price path, which is not directly related to the dependence-treatment (e.g. whether it ends with a few positive returns of stock 1). We solve this problem by randomizing the order of pair-wise observations for each participant's representative sample.

Experimental tasks: Participants are randomly assigned to one of the treatment sequences in a counterbalanced design.[7] After a short introduction, including instructions and a comprehension question, participants view 10×10-year price paths and return series for the two stocks. The 100 observations form a representative joint distribution for the treatment, but the order is randomized by participant. Then, they are asked how much of 10'000 € they want to invest into stocks 1 and 2. Finally, participants answer questions about the

[6] This is a weak form of experience sampling, which might influence results, as discussed in Section 1.

[7] In experiment, 1 there are 6 possible sequences for treatments 1, 2 and 3: 1-2-3, 1-3-2, 2-1-3, 2-3-1, 3-1-2, and 3-2-1. In experiments 2, 3 and 4, there are 2 possible sequences for treatments 1 and 2: 1-2 and 2-1.

dependence between stocks 1 and and 2.[8] Stock 1 offers an average return of 5%, whereas stock 2's return distribution exhibits an average of only 4% achieved through a shift of stock 1's distribution by 1%, so that all higher moments (e.g. volatility or skewness) are equal across stocks. Stock 2 should thus only be interesting because of its diversification potential. To incentivize participants, they get a fraction of $\frac{1}{1000}$ of a simulated one-year payoff of their selected portfolio (payoffs range from 6.40 € to 13.50 € with an average of 10.47 € over all experiments; each session of the experiments took around one hour). To test our hypotheses on beliefs (H_{11} and H_{21}) we directly ask for the dependence between stocks 1 and 2 (e.g. the overall dependence, dependence in extreme and moderate returns). To test our hypotheses on investors' portfolio choice (H_{12} and H_{22}), we check whether participants invest more in stock 2—the stock with a lower return—when they perceive dependence between the stocks to be lower. The investment choice is made before questions about beliefs are asked.

Control variables: To improve the efficiency of some estimates, a number of control variables are collected at the end of the experiment (e.g. age, financial literacy and numeracy). Some of these variables (e.g. financial literacy) are additionally used as interaction variables with the main independent variable (the dependence treatment).[9]

2.2 Experiment 1: Varying Linear Dependence

Stimuli: In experiment 1, we test the effects of varying linear dependence on beliefs and diversification choices (H_{11} and H_{12}). Correlation is -0.6 for treatment 1, 0.2 for treatment 2 and 0.6 for treatment 3.[10] The conditional expectation of stock 1's return is linear in stock 2's return (i.e. $E(r_1|r_2) = a + b \cdot r_2$, see joint distributions in Table 2 and conditional expectations in Figure 1). The co-movement between returns increases from treatment 1 to treatment 3, regardless of whether participants focus on frequent, moderate returns or rare, extreme returns. Hence, we expect participants to perceive an increase in dependence from treatment 1 to treatment 3 (H_{11}). Consequently, we expect participants to diversify

[8] Internet Appendix D shows an overview of the experiment. The exact instructions and questions from the experiment are reported in Internet Appendix E.

[9] Internet Appendix C shows an overview of the outcome variables (Panel A) and control variables (Panel B) collected in these experiments.

[10] The non-zero correlation (0.2) in treatment 2 is due to our requirement that probabilities for all states have round percentage values, so that a representative distribution with $10 \times 10 = 100$ observations can be used. We opted for a slightly positive correlation, instead of the also feasible slightly negative correlation of -0.2, since in financial markets positive correlations are more common.

less as correlation increases (H_{12}). Figure 2 shows two of the 10×10-year draws sampled by participants for treatments 1 and 3, respectively. Note that the order of pairwise returns in the 10×10-year sample is randomized for each participant, so that it is uncertain how many of the other participants get to see exactly these price paths. Figure 3 shows the optimal investment in stock 2 for an expected utility maximizing investor with constant relative risk aversion (CRRA) at relative risk aversion from 0.5 to 10. The increase in correlation from treatment 1 to 3 leads to a a lower optimal investment in stock 2. This can be expected as stock 2's return distribution is just stock 1's return distribution minus 1%, so that the main reason for a reasonably risk-averse CRRA investor to buy stock 2 is to diversify risk. Since the diversification potential of stock 2 decreases as correlation increases, the optimal investment in stock 2 decreases with correlation. Increased relative risk aversion leads to a higher optimal investment in stock 2. The return-difference of 1% between stocks 1 and 2 was selected so that only unreasonably low levels of relative risk aversion lead to the boundary solution of zero investment in stock 2.

[INSERT TABLE 1 ABOUT HERE]

[INSERT TABLE 2 ABOUT HERE]

[INSERT FIGURE 2 ABOUT HERE]

[INSERT FIGURE 3 ABOUT HERE]

Data and participants: Experiment 1 was conducted at a lab for experimental economics with 127 participants. The participant pool consists mostly of university students. Summary statistics about the participants are reported in Panel A of Table 1. Note that there is considerable variation in financial literacy and numeracy scores. This enables us to test whether the perception of dependence and investment decisions change for more financially literate or numerate participants.

Discussion of results: Table 3 reports participants' beliefs about dependence.[11] In summary, the findings lend support to hypothesis H_{11}: participants (correctly) believe dependence increases from treatment 1 to treatment 3. The exact questions asked are included

[11]All outcome variables, which are not reported in the main tables are reported in Internet Appendix A and discussed in Internet Appendix B.

in the tables and listed in Internet Appendix E. Panel A shows that the majority (94 out of 127) of participants understand that stocks 1 and 2 move in opposite directions in treatment 1, where correlation is -0.6. In treatment 3, where correlation is +0.6, the majority (98 out of 127) understand that stocks 1 and 2 move together. Mean beliefs about dependence on a scale from 1 (Stocks 1 and 2 move ...in opposite directions) to 5 (...together) increase from 2.22 to 3.41 from treatment 1 to 2, and then to 3.86 for treatment 3. These increases are statistically significant. Panels B1 and B2 show that beliefs about the frequency of co-movement also change in accordance with the treatments' true frequencies of co-movement: participants estimates for the frequency of co-movement significantly increase as correlation increases. For treatment 2 the average estimated frequency of co-movement (58% in B1 and 56% in B2) is relatively close to the treatment's true frequency of co-movement (60%). For treatments 1 and 3 the estimated frequencies are biased towards 50%. In treatment 1 the true probability of co-movement is 20%, but participants' average estimates are at 35% (Panel B1) and 38% (Panel B2). In treatment 3 the true probability of co-movement is 80%, but participants' average estimates are at 69% (Panel B1) and 68% (Panel B2).

[INSERT TABLE 3 ABOUT HERE]

Participants' beliefs about dependence in extreme versus moderate returns are reported in Panels C and D of Table 3. Again, participants seem to understand how dependence changes as correlation increases. Panels C1 and C2 show that the majority of participants believe that dependence in extreme returns is negative in treatment 1 and positive in treatment 3. Treatment effects on average beliefs about dependence in extreme returns are highly statistically significant for all pairwise comparisons. Panels D1 and D2 exhibit the same pattern for participants' beliefs about dependence in moderate returns. Although effects are somewhat weaker they are still highly statistically significant. Note that from this experiment we cannot tell whether participants actually understood dependence in both domains, extreme and moderate returns. It may be that participants just understand dependence in one of the domains and project this belief onto the other domain. Since dependence is linear, this would not lead to biased beliefs. In experiment 2 we vary non-linear dependence to test whether participants understand both or just one of the two domains of dependence. All in all, the evidence in Table 3 is in line with H_{11}: Participants are able to perceive changes in linear dependence.

Next, we analyze whether linear dependence influences investment decisions. We would expect participants to diversify more when correlation decreases (H_{12}). Hence we would expect them to invest more in stock 2 in treatment 1 than in treatment 2, and more in treatment 2 than in treatment 3. Table 4 shows that this is indeed the case. Participants invest an average of 3'186€ out of 10'000€ into stock 2 in treatment 3, where correlation is at +0.6. For treatment 2 (correlation of +0.2) the investment in stock 2 increases by 707€ to 3'893€. And for treatment 1 (correlation of -0.6) participants diversify the most at 4'112€. The treatment effects from treatment 3 to treatments 1 and 2 are statistically significant at the 1%-level, whereas the treatment effect from treatment 2 to 1 is statistically insignificant.[12] Figure 3 shows that the average levels of investment in stock 2 are consistent with the optimal decision of a CRRA-investor with relative risk aversion between 2 and 5. Estimates of relative risk aversion from survey and field data regularly put it in this vicinity.[13] Note that these results are surprising, since previous research mostly found evidence in line with correlation neglect.

[INSERT TABLE 4 ABOUT HERE]

We now analyze some characteristics of participants that might be associated with the diversification decision. A variable one would expect to influence the diversification decision is risk aversion. More risk-aversion should lead to a higher level of investment in stock 2. In specification (2) of Table 4 we add participants' self-assessed risk aversion (standardized to have a mean of zero and standard-deviation of one) as an explanatory variable. Indeed a one standard-deviation increase in risk aversion is associated with a 503€ increase in diversification.[14] Other variables that might influence the diversification decision are financial

[12]Regressing the investment in stock 2 on beliefs about dependence leads to qualitatively similar results. However, since these beliefs might co-vary with the investment decision independent of variation in dependence (they are endogenous), we rather analyze differences between treatments (the exogenous variation in dependence) directly.

[13]Friend and Blume (1975) use survey data on household asset holdings and find relative risk aversion 'probably in excess of two'. Metrick (1995) estimates risk aversion close to zero, using behavior on the game show 'Jeopardy!'. Kimball, Sahm, and Shapiro (2008) estimate a value of approximately eight based on hypothetical income gambles elicited through a survey. Aarbu and Schroyen (2014) use choices among hypothetical income lotteries in a Norwegian survey and arrive at a value of three to four. Paravisini, Rappoport, and Ravina (2015) use micro-lending data and get a relative risk aversion of close to three.

[14]Note that including characteristics of participants as additional variables does not change estimates for our treatment effects. This is because every participant goes through both treatments, so that the treatment dummies are orthogonal to characteristics of participants.

literacy and numeracy. In specification (3) of Table 4 we add both (again standardized) to the regression. Whereas numeracy does not significantly influence the investment in stock 2, financial literacy seems to decrease the level of diversification. A one standard-deviation increase in financial literacy decreases the investment in stock 2 by 269 €.[15] This decrease in diversification might be driven by less 'naive diversification' (usage of the 1/N-heuristic) by financially literate participants. Incidentally, the treatment effects in our experiments cannot be explained by 'naive diversification', since a bias towards 1/N should equally affect investment decisions in both treatments.

Even though financial literacy and numeracy do not have a robust influence on the level of diversification they could influence the treatment effects, i.e. the difference in diversification from treatment to treatment. To test this, we add interaction effects between our treatment dummies, financial literacy and numeracy (see specification (4) of Table 4). Even though there is strong variation in both variables (see summary statistics in Table 1), we do not find statistically significant interaction effects. A qualifier: confidence intervals include economically significant values.[16] All in all, the evidence in Table 4 is in line with H_{12}: Participants diversify more as linear dependence decreases.

2.3 Experiment 2: Varying Non-Linear Dependence I

Stimuli: In experiment 2, we test the effects of varying non-linear dependence on beliefs and diversification choices (H_{21} and H_{22}), i.e. we test whether participants perceive dependence based on extreme (but rare) or frequent (but moderate) observations. Correlations between the two stocks are set to zero in both treatments. Although correlation is thus the same, a strong variation in dependence between extreme versus moderate returns across treatments is achieved: treatment 1 exhibits negative dependence in extreme returns and positive dependence in moderate returns, while treatment 2 exhibits positive dependence in extreme returns and negative dependence in moderate returns (see joint distributions in

[15] In unreported robustness tests, we replace the financial literacy score by a dummy that indicates whether the one question related to diversification from the financial literacy test—item (5)—was answered correctly. Results do not qualitatively change.

[16] In unreported tests we find that adding control variables does not qualitatively change our results. We add: self-assessed statistics knowledge, age, gender, a dummy that is one if the participant owns stocks/equity-funds, a dummy for participants who indicate interest in financial markets and a dummy for having attended a university statistics course.

Table 5, conditional expectations are displayed in the lower Panel of Figure 1). Since dependence in the domain of extreme returns is positive when dependence in the domain of moderate returns is negative (and vice versa) we can differentiate participants who understand dependence in only one of these domains from those who understand it in only the other domain, even if they project their beliefs onto the domain they do not understand. If participants rather focus on dependence in extreme returns, we expect them to perceive an increase in overall dependence from treatment 1 to treatment 2, since dependence in extreme returns changes from perfectly negative to perfectly positive from treatment 1 to treatment 2. We particularly expect participants to correctly answer questions about dependence in extreme returns. In contrast, if participants rather focus on dependence in moderate returns, we expect them to perceive a decrease in overall dependence from treatment 1 to treatment 2, since dependence in moderate returns changes from perfectly positive to perfectly negative from treatment 1 to treatment 2. Participants should then be able to answer questions about dependence in moderate returns particularly well. Consequently, we expect participants to diversify less in treatment 2, relative to treatment 1, if they focus on extreme returns. Vice versa, if they focus on moderate returns, we expect them to diversify more in treatment 2. Figure 4 shows the optimal investment in stock 2 for an expected utility maximizing investor with constant relative risk aversion (CRRA) at relative risk aversion from 0.5 to 10. Since correlation between returns and marginal distributions (means and variances) do not change from treatment 1 to treatment 2, the difference between optimal investments in stock 2 from treatment 1 to 2 is small relative to experiment 1.

[INSERT TABLE 5 ABOUT HERE]

[INSERT FIGURE 4 ABOUT HERE]

Data and participants: Like experiment 1, experiment 2 was conducted at a lab for experimental economics. Summary statistics about the 94 participants are reported in Panel B of Table 1. They are similar to the summary statistics from experiment 1. There is no overlap between the sets of participants in experiments 1 and 2.

Discussion of results (beliefs): We first analyze participants' beliefs about dependence, i.e. we test whether participants' perception of dependence is influenced by changes in non-linear dependence (H_{21}). In summary, the findings are in line with the hypothesis that participants correctly adjust their beliefs to changes of dependence in moderate returns, whereas they either do not understand dependence in extreme returns or even incorrectly project their beliefs about dependence in moderate returns onto extreme returns. Table 6 reports participants' beliefs about dependence. Participants believe overall dependence to decrease from treatment 1 to treatment 2. Dependence in extreme returns increases from treatment 1 to treatment 2, but dependence in moderate returns decreases. Panel A reports that—on a scale from 1 (Stocks 1 and 2 move ...in opposite directions) to 5 (...together)—participants expect stocks 1 and 2 to co-move (at an average of 3.55) in treatment 1, whereas they expect stocks 1 and 2 to move in opposite directions (at an average of 2.63) in treatment 2. The difference between average categories is statistically significant at the 1% level. Panel B shows that the estimated frequency of co-movement decreases from treatment 1 (72% in Panel B1 and 62% in Panel B2) to treatment 2 (37% in Panel B1 and 41% in Panel B2). The treatments' true frequencies of co-movement are 90% and 10%, respectively, so that there is a strong bias towards 50%. However, treatment effects have the hypothesized sign and are statistically significant at the 1% level.

[INSERT TABLE 6 ABOUT HERE]

Of course, the above results do not yet show that participants do not understand dependence in extreme returns. It might be that the question about overall dependence (Panel A of Table 6) is understood as a question about the frequency of co-movement (Panel B of Table 6), regardless of the magnitude of returns. Hence, we ask participants directly for their beliefs about dependence conditional on the magnitude of returns. Panels C and D of Table 6 show participants' beliefs about dependence in extreme versus moderate returns. Panel A reports the participants' beliefs about dependence in extreme returns. On the one hand, for treatment 1, stock 2 *always* moves in the *opposite* direction of stock 1 in extreme returns. On the other hand, for treatment 2, stock 2 *always* moves in the *same* direction as stock 1 in extreme returns. In spite of this clear, deterministic conditional dependence most participants cannot correctly answer the questions about dependence in extreme returns. In some cases the number of participants who select the category opposite to the correct one ('decrease' when 'increase' is correct and vice versa) is larger than the number of participants who select the correct category. There is no statistically significant treatment effect. In contrast, Panel B shows that participants' beliefs react correctly to the decrease of dependence in moderate returns from treatment 1 to treatment 2. Few participants (between 8 and 16 out of 94) wrongly believe dependence in moderate returns to be negative when it is actually positive or vice versa. Thus, whereas the average participant understands dependence in frequent, moderate returns, she does not understand dependence in infrequent, extreme returns.

Heterogeneous beliefs about extreme returns: There are several potential reasons why there is no effect of this extreme switch in dependence of extreme returns on participants' *average* beliefs about them. Since our hypothesis on investment decisions (H_{22}) depends on participants' perceived dependence, it is important to analyze these reasons. It may be that none (or only very few) of the participants understand dependence in extreme returns. In this case, one would expect a large number of participants to check the middle category (between 'decrease' and 'increase') in their answers to the questions about extreme dependence. However, the patterns in Panel C of Table 6 show that many participants do not check the middle category. Actually, for 3 out of 4 questions, the middle category is selected less frequently than either one of the other categories. This v-pattern could be explained by two counterbalancing types of participants, in addition to the participants who have 'no idea' about dependence in extreme returns. Type 1 participants project their beliefs about frequent, moderate returns onto infrequent, extreme returns and thus systematically select the category opposite to the correct one. Type 2 participants have no idea about dependence in extremes and tend to select the middle category. Type 3 participants understand dependence in extreme returns and systematically select the correct category. We empirically identify Type 1 participants as the ones who answer 'decrease' if the correct answer is 'increase' and vice versa in at least 3 out of 4 questions about dependence in extremes (18 out of 94 participants). Type 3 participants are identified as the ones who correctly answer at least 3 out of 4 questions about dependence in extremes (16 out of 94 participants). The other participants are identified as Type 2 (60 out of 94 participants).[17]

Discussion of results (choice): Next, we analyze the impact of non-linear dependence on participants' investment decisions, i.e. hypothesis H_{22}. This hypothesis depends on the participants' beliefs about dependence. The perception of dependence for Type 1 and Type 2 participants is driven by moderate returns. Hence, for them (78 out of 94 participants) we expect the investment in stock 2 to increase as dependence in moderate returns decreases

[17]Note that an analogous classification for beliefs about moderate dependence is unnecessary, because hardly any participants systematically answer questions about moderate dependence incorrectly.

from treatment 1 to treatment 2. The perception of dependence for Type 3 participants may be driven by both moderate or extreme returns, so that it is not clear, how they should react to the treatment. Hence, the following analysis of participants' investment decisions is done separately for Type 3 participants. Table 7 reports how participants' investment decisions change as non-linear dependence changes. Specifications (1) and (2) show that Type 1 and 2 participants increase their investment in stock 2 from 3'619 € to 4'179 € as moderate dependence decreases from treatment 1 to treatment 2. The difference in investment of 561 € is statistically significant at the 5% level. In contrast, specifications (1) and (3) show that Type 3 participants decrease their investment in stock 2 from 3'531 € to 3'018 € as extreme dependence increases from treatment 1 to treatment 2. The treatment effect for Type 3 participants is not statistically significant, maybe owing to their low frequency (16 out of 94 participants). In specification (4) we check whether the treatment effect on Type 1 and 2 participants changes for participants with more financial literacy or numeracy. In spite of strong variation in financial literacy and numeracy (see summary statistics in Table 1), interaction effects are statistically insignificant.[18] All in all, the evidence in Table 7 is in line with H_{22}: Participants take perceived dependence into account in their portfolio selection decision.

[INSERT TABLE 7 ABOUT HERE]

2.4 Experiment 3: Varying Non-Linear Dependence II

Stimuli: In experiment 3, we check whether our insights from experiment 2—that participants focus on dependence in moderate returns when forming beliefs and making diversification choices—are robust under a more extreme treatment. We now let correlation increase with dependence in extreme returns from treatment 1 to treatment 2, while dependence in moderate returns decreases. This lets us pit the hypothesis that participants focus on moderate returns against the prediction from Markowitz (1952) that correlation matters. Specifically correlation increases from -0.21 in treatment 1 to +0.21 in treatment 2 while—as in experiment 2—dependence in moderate returns decreases from perfectly positive to

[18] In unreported robustness tests, we replace the financial literacy score by a dummy that indicates whether the one question related to diversification from the financial literacy test – item (5) – was answered correctly. Results do not change.

perfectly negative, and dependence in extreme returns increases from perfectly negative to perfectly positive. We achieve this change in correlations by making both marginal distributions more extreme, shifting the extreme returns outwards by 7% (joint distributions are reported in Table 8). The extremeness of returns, −33% (+42%) p.a. for the 5 out of 100 lowest (highest) returns, is now comparable to historical values. As an illustration, the average of S&P 500 returns in the worst (best) 5 years from 1928 to 2015 is −33.35% (+47.36%). If our insights from experiment 2 hold, participants will still understand dependence in moderate returns while not understanding dependence in extreme returns. Consequently they should diversify less when moderate dependence increases from treatment 1 to treatment 2, even though correlation decreases. This would be a surprising result as it contradicts prescriptions for risk-averse investors under standard utility functions. Figure 5 shows the optimal investment in stock 2 for an expected utility maximizing investor with constant relative risk aversion (CRRA) at relative risk aversion from 0.5 to 10. In contrast to experiment 2, where correlation stayed constant at zero across treatments leading to hardly different optimal diversification choices, correlation now increases from treatment 1 to treatment 2. Therefore, a CRRA investor optimally diversifies less in treatment 2 compared to treatment 1. For instance at a relative risk aversion of 2, a CRRA investor's investment goes from around 4000 € in treatment 1 to around 3200 € in treatment 2. Hence, the variation in correlation is large enough to warrant economically significant differences in diversification from a normative standpoint.

[INSERT TABLE 8 ABOUT HERE]

[INSERT FIGURE 5 ABOUT HERE]

Data and participants: Like experiments 1 and 2, experiment 3 was conducted at a lab for experimental economics. Summary statistics about the 107 participants are reported in Panel C of Table 1. They are similar to the summary statistics from experiments 1 and 2. There is no overlap between the sets of participants in experiments 1, 2 and 3.

Discussion of results: We first analyze participants' beliefs about dependence, i.e. we test whether participants' perception of dependence is influenced by changes in non-linear dependence (H_{21}). In summary, the findings are in line with results from experiment 2. Participants' beliefs about dependence in moderate returns are consistent with the treatments, whereas most participants do not understand dependence in extreme returns. Table 9 reports participants' beliefs about dependence. Participants believe overall dependence to decrease from treatment 1 to treatment 2. Dependence in extreme returns increases from treatment 1 to treatment 2, but dependence in moderate returns decreases. Panel A reports that—on a scale from 1 (Stocks 1 and 2 move ...in opposite directions) to 5 (...together)—participants expect stocks 1 and 2 to co-move (at an average of 3.39) in treatment 1, whereas they expect stocks 1 and 2 to move in opposite directions (at an average of 2.63) in treatment 2. The difference between average categories is statistically significant at the 1% level. Panel B shows that the average estimated frequency of co-movement decreases from treatment 1 (71% in Panel B1 and 61% in Panel B2) to treatment 2 (40% in Panel B1 and 44% in Panel B2). The treatments' true frequencies of co-movement are 90% and 10%, respectively, so that—as in experiment 2—there is a strong bias towards 50%. However treatment effects have the hypothesized sign and are statistically significant at the 1% level.

[INSERT TABLE 9 ABOUT HERE]

We then ask participants directly for their beliefs about dependence conditional on the magnitude of returns. Panels C and D of Table 9 show participants' beliefs about dependence in extreme versus moderate returns. Panel C reports the participants' beliefs about dependence in extreme returns. As in experiment 2, participants have trouble correctly answering questions about dependence in extreme returns, even though it is deterministically negative in treatment 1 and positive in treatment 2. For one of the two questions about dependence in extreme returns, there is a treatment effect with the correct sign, which is statistically significant at the 10% level. However, the magnitude of the effect is relatively small and this result cannot be confirmed in our second question on extreme returns. A large number of participants (between 26 and 42 out of 107) check the answer opposite to the correct one, again consistent with them projecting their (correct) beliefs about dependence in moderate returns onto extreme returns. In contrast, Panel D shows that participants' beliefs react correctly to the decrease of dependence in moderate returns from treatment 1 to treatment 2. Few participants (between 8 and 10 out of 107) wrongly believe dependence in moderate returns to be negative when it is actually positive or vice versa. Thus, whereas the average participant understands dependence in moderate returns, she does not understand dependence in extreme returns. All in all, the evidence from Table 9 is in line with our finding from experiment 2: Dependence is on average perceived based on frequent, moderate observations.

Next, we analyze the impact of our treatments on participants' investment choices. The results lend further support to our insights from experiment 2. Participants diversify more as dependence in moderate returns decreases from treatment 1 to treatment 2, even though correlation and dependence in extreme returns increase. As in experiment 2 we split participants into two groups: those that do not understand dependence in extreme returns (Types 1 and 2: 86 out of 107 participants) and those that understand it (Type 3: 21 out of 107 participants). The prediction for Types 1 and 2 is clear. These participants do not understand dependence in extreme returns, but mostly do understand dependence in moderate returns, which decreases from treatment 1 to treatment 2. Hence, we expect them to diversify more in treatment 2. This is indeed the case: Specifications (1) and (2) of Table 10 show that Type 1 and 2 participants increase their investment in stock 2 from 3'154 € to 4'077 € as moderate dependence decreases from treatment 1 to treatment 2. The difference of 923 € is statistically significant at the 1% level. In contrast, the prediction for Type 3 participants is not straightforward. They seem to understand dependence in moderate and extreme returns, so that any of these could drive their decision. As discussed above, a CRRA investor would base her decision mostly on correlation and diversify less in treatment 2. On the other hand an investor with a strong preference to be well diversified most of the time would diversify more in treatment 2. Even though there are just 21 Type 3 participants, there is a statistically significant positive treatment effect from treatment 1 to treatment 2 (at the 5% level). Hence, these participants' diversification choice seems to also be driven by dependence in frequent, moderate returns. As for the previous experiments, Specification (4) shows that there is no significant interaction between our treatment effects and financial literacy or numeracy.[19] All in all, the evidence in Table 10 is in line with H_{22} and our insights from experiment 2: Participants take perceived dependence into account in their portfolio selection decision. However, they only understand dependence in moderate returns, not in extreme returns. In line with their perception of dependence, they diversify more as dependence in moderate returns decreases, even though correlation increases along

[19] In unreported robustness tests, we replace the financial literacy score by a dummy that indicates whether the one question related to diversification from the financial literacy test – item (5) – was answered correctly. Results do not change.

with dependence in extreme returns. As discussed above, this goes against predictions under standard utility functions.

[INSERT TABLE 10 ABOUT HERE]

2.5 Experiment 4: Returns vs. Prices

Stimuli: In experiment 4, we analyze how our results are influenced by the way we display information on the stocks. Both numerical returns and price paths are common pieces of information in realistic investment decisions. However, often only one of these is provided. In contrast to experiments 1 to 3 we display only return histories for one part of the participants (the return group), and only price paths for the other part (the price group; see examples in Figure 6). We use the same dependence treatments 1 and 2 as in experiment 3 (see Table 8). Hence correlation increases with dependence in extreme returns from treatment 1 (correleation of -0.21) to treatment 2 (correlation of +0.21), while dependence in moderate returns decreases. Since only the display of information is changed—not dependence treatments—the optimal investment in stock 2 for a CRRA investor does not change (see Figure 5). Optimally, participants would diversify less in treatment 2 compared to treatment 1, because diversification benefits decrease as correlation increases.

[INSERT FIGURE 6 ABOUT HERE]

Data and participants: Like experiments 1 to 3, experiment 4 was conducted at a lab for experimental economics. Summary statistics about the 138 participants are reported in Panel D of Table 1. They are similar to the summary statistics from the previous experiments.

Discussion of results: We first analyze participants' beliefs about dependence, i.e. we test whether participants' perception of dependence is influenced by changes in non-linear dependence (H_{21}). Table 11 reports participants' beliefs about dependence. The findings for the price group are in line with results from experiments 2 and 3: Participants' beliefs about dependence in moderate returns are consistent with the treatments (see right-hand side of Panel D in Table 11), whereas most participants do not understand dependence in extreme returns (see right-hand side of Panel C). In contrast, participants from the return group are significantly more likely to also understand dependence in extreme returns (left-hand side of

Panel C).[20] In spite of this better understanding of dependence in extreme returns, the return group's overall dependence assessment is still driven by dependence in moderate, frequent returns: They believe overall dependence to decrease from treatment 1 to treatment 2 (see Panel A in Table 11). Hence, the evidence from Table 11 is in line with our finding from experiments 2 and 3 for both, the return and the price group: Dependence is on average perceived based on frequent, moderate observations.

Throughout Table 11 effect sizes are larger within the return group as compared to the price group. Furthermore the significantly better understanding of dependence in extreme returns compared to experiments 2 and 3 suggests that displaying return series without price paths (i.e. *less* information) leads to a better understanding of dependence. Consistent with a better understanding of dependence in experiment 4's return group, these participants assess their level of informedness and confidence in their decision as significantly higher.[21]

[INSERT TABLE 11 ABOUT HERE]

Next, we analyze the impact of our treatments on participants' investment choices. Using the same method as in experiments 2 and 3 we split participants into two groups: those that do not understand dependence in extreme returns (Types 1 and 2) and those that understand it (Type 3). The prediction for Types 1 and 2 is clear. These participants do not understand dependence in extreme returns, but mostly do understand dependence in moderate returns. Dependence in moderate returns decreases from treatment 1 to treatment 2. Hence, we expect Type 1 and 2 participants to diversify more in treatment 2. This is indeed the case: For the return group, Specification (1) of Table 12 shows that Type 1 and 2 participants increase their investment in stock 2 from 3'374 € to 4'197 € as moderate dependence decreases from treatment 1 to treatment 2. The difference of 824 € is statistically significant at the 1% level. For the price group, the treatment effect for Types 1 and 2 is also positive, but economically smaller at 293 € and statistically insignificant, see Specification (3). The prediction for Type 3 participants is not straightforward. They seem to understand dependence in moderate *and* extreme returns, so that any of these could drive their decision. The 28 participants of Type 3 in the return group diversify significantly more when dependence in frequent, moderate

[20]Framing effects related to prices vs. returns have been documented before, e.g. Glaser, Langer, Reynders, and Weber (2007) find that asking for return forecasts leads to significantly more optimistic forecasts than asking for price forecasts when prices trend upward.

[21]These further results are reported in Internet Appendix A and discussed in Internet Appendix B

returns is lower, see Specification (2). This is consistent with our results from experiment 3: In spite off understanding dependence in extreme returns, Type 3 participants seem to base their diversification decision on dependence in moderate returns, suggesting there is more than biased beliefs to our general result that dependence in frequent, moderate returns matters for diversification decisions. In contrast, the 15 participants of Type 3 in the price group diversify significantly more when dependence in extreme, rare returns is lower, see Specification (4). Hence, although beliefs about dependence are similar for all these Type 3 participants, the participants who view price paths choose to diversify away extreme, rare variations, whereas participants who view return series choose to diversify away frequent, moderate variations. As a consequence, the treatment effect from treatment 1 to treatment 2 (over all Types) increases by 992 € as we go from the price group to the return group. This effect is significant at the 1% level, see Specification (5).

[INSERT TABLE 12 ABOUT HERE]

All in all, the evidence for the participants who view return series, and for the participants who view price paths *and* are unable to correctly answer questions about dependence in extreme returns is in line with hypothesis H_{22} and our results from experiments 2 and 3: Participants take perceived dependence into account in their portfolio selection decision. They diversify more as dependence in moderate returns decreases, even though correlation increases along with dependence in extreme returns. In contrast, the few participants who view price paths *and* are subsequently able to correctly answer questions about dependence in extreme returns diversify more as dependence in extreme returns decreases along with correlation. The flipped sign of our treatment effect for these 15 (out of 76) participants in the price group is puzzling and warrants future research on presentation modes and investment decisions. Maybe the graphical display of a crash in a stock's price leads to a higher decision weight for this extreme state than the same information as a numerical return, e.g. '-33%'. In any case, the effect of dependence between asset returns on beliefs about dependence and investment decisions is influenced by the way information is presented. Given the choice of viewing price paths or return series (as in experiments 1, 2 and 3), participants' investment choices are similar to choices when they are only given return series. They seem to automatically use returns to make their investment decision, maybe because they find returns to be more informative. This would be consistent with the higher levels of informedness and confidence they state for their investment decision in the return group relative to the price group of experiment 4 (see discussion in Internet Appendix B).

3 From the Lab to Reality: The Perception of Dependence and Stock Returns

Participants of our laboratory experiments diversify more at lower frequencies of co-movement, i.e. when stock returns tend to be of opposite signs, consistent with a simple counting heuristic. However, they do not take into account correlations or betas, as suggested by classical theory (Markowitz (1952) and Sharpe (1964)). If enough investors use the frequency of co-movement between stock and market returns as a risk measure, it might be priced. Stocks that frequently co-move with the market are unattractive to them and should have lower prices and higher future returns to reward investors. We test this implication using 1963-2015 CRSP data of US common shares from the NYSE and AMEX.[22] To avoid microstructure issues, we exclude stocks with last-month prices below $1.[23]

For our main tests we measure the frequency of co-movement 'CoMove' as the fraction of return observations with equal signs of monthly stock and S&P 500 market returns from the last 36 months, i.e. the fraction of monthly observations with ($r_i > 0$,$r_m > 0$) or ($r_i < 0$,$r_m < 0$). We select the S&P 500 as our market index, since due to its popularity its returns are highly visible to a large number of investors.[24] The most important control variable for our tests is the seminal measure of systematic risk, β, as introduced by Sharpe (1964). We measure β using the last year's daily stock and value-weighted market returns.[25] In our first test, we double sort stocks into quintile portfolios by β first and CoMove second. Then we pool stocks across β quintiles and within CoMove quintiles to obtain a portfolio sort by CoMove controlling for β. Results are reported in Panel A of Table 13.

[22] You will find summary statistics for our main variables in Table A6 of Internet Appendix A.

[23] In robustness tests, we show that our findings are qualitatively the same when we include NASDAQ stocks, exclude small-firm stocks or exclude stocks with prices below $5, see Panel B of Table A7 in Internet Appendix A.

[24] In robustness tests, we show that our findings are qualitatively the same, if we measure CoMove based on the last 52 weekly returns or the last 260 daily returns, or if we use CRSP's value-weighted market return instead of the S&P 500 return, see Table A7 in Internet Appendix A.

[25] Using daily returns to estimate β is common. In unreported tests we check that using the last 36 or 60 monthly returns instead does not qualitatively change results.

[INSERT TABLE 13 ABOUT HERE]

We first analyze the relation between CoMove and stock returns for the full sample from 1963 to 2015. The average portfolio return increases monotonically from 0.60% to 0.83% from the low to the high CoMove quintile. Thus, high CoMove stocks have outperformed low CoMove stocks by 0.23% per month (2.76% per year) between 1963 and 2015. Controlling for the Carhart (1997) four factor model leads to an alpha of 4.30% per year, which is statistically significant at the 1% level (t-stat of 4.20).[26] A sample split into the 1963-1988 (middle Panel) and 1989-2015 (lower Panel) subperiods reveals, that the premium is driven by post-1989 returns. For the second half of our sample high CoMove stocks have outperformed low CoMove stocks by 5.53% (6.08%) per year (adjusted for the Carhart (1997) factors). This outperformance is statistically significant the the 1% level at t-statistics above 3, the conservative hurdle suggested by Harvey, Liu, and Zhu (2016).

[INSERT FIGURE 7 ABOUT HERE]

Figure 7 displays cumulative Carhart (1997) alphas of our high-minus-low CoMove strategy and analogous alphas for a high-minus-low β strategy.[27] Historically, β is not priced (see e.g. Fama and French (2004)). However, sorting by β leads to a high exposure to the equity premium, which has historically been significantly positive. Hence, controlling for the market return leads to an economically significant negative alpha of the high-minus-low β strategy over the last 50 years.[28] In contrast, the CoMove strategy consistently delivers a positive premium over the last 50 years. In line with our previous evidence, over 75% of the cumulative alpha of the CoMove strategy accumulates in the second half of our sample, after 1988.

We also control for a battery of alternative factors that can have an impact on the cross-section of stocks and that are discussed in the literature. Monthly alphas from all these regressions are shown in Panel B of Table 13. In the first (fourth) line, we repeat the results

[26] t-statistics are based on Newey and West (1987) standard errors with one lag.

[27] The high-minus-low β strategy is built analogously, sorting by CoMove first and by β second, and then pooling stocks across CoMove quintiles and within β quintiles. The figure hardly changes when we sort by β without controlling for CoMove.

[28] Frazzini and Pedersen (2014) show how the insignificant pricing of β can be used to build a market-neutral 'betting against beta' strategy, which is profitable before controlling for the strategy's market exposure.

based on raw returns (Carhart (1997) 4-factor alphas) for easy comparison. In lines two and three we report CAPM 1-factor (1F) and Fama and French (1993) 3-factor (3F) alphas. In other lines, in addition to the four factors from the Carhart (1997) model, we include (i) the short- and long-term reversal factors from Kenneth French's data library, (ii) the Frazzini and Pedersen (2014) betting-against-beta (BAB) factor, (iii) the Kelly and Jiang (2014) tail risk factor, (iv) the Pástor and Stambaugh (2003) (PS) liquidity factor, (v) the Sadka (2006) (fixed-transitory and variable-permanent) systematic liquidity factors, and (vi) the Hirshleifer and Jiang (2010) undervalued-minus-overvalued (UMO) factor. Additionally, we run the new Fama and French (2015) five factor model. Measured over the 1963-2015 period, the CoMove premium is always positive and statistically significant. Again, the alpha is usually higher when we restrict our analysis to the later half of our sample. From 1989 to 2015, the premium of high-CoMove stocks over low-CoMove stocks varies between 4.41% per year and 7.09% per year. It is always statistically significant at the 1% level.

[INSERT FIGURE 8 ABOUT HERE]

One reason for the higher CoMove premium during the later half of our sample may be the increase in public attention towards portfolio and risk management during the sample period. Figure 8 displays the percentage of New York Times articles containing words related to risk (e.g. 'correlation' or 'volatility'), normalized by the number of articles containing the word 'stocks'. The number of articles using terms related to risk has increased by an order of magnitude since 1963. Maybe the number of investors using their perceived dependence between stock and market returns (CoMove) as one factor to select stocks has increased accordingly. This would explain the higher CoMove premium during the later half of our sample.

[INSERT TABLE 14 ABOUT HERE]

To control for further stock and firm characteristics, that are related to stock returns and might be related to CoMove, we use Fama and MacBeth (1973) regressions. Results are reported in Table 14. In specification (1) we control for systematic risk β, firm size, book/market ratios, and last year's returns (momentum). The coefficient of CoMove is statistically significant at the 1% level (t-statistics of 4.78). The inter-decile spread of CoMove is 0.25, so that the coefficient of 0.0118 implies a monthly return premium of 0.30%

of high-quintile minus low-quintile stocks, controlling for systematic risk, size, value, and momentum. This is in line with our above evidence from factor models.

We first control for measures of asymmetric (downside vs. upside) systematic risk. Maybe the frequency of comovement is particularly high for stocks that crash when the market crashes. The downside risk literature shows that stocks that crash with the market tend to have higher returns. In specification (2), we control for downside and upside beta (as in Ang, Chen, and Xing (2006)). On the stock level, these are not priced when we control for the Carhart (1997) predictors, consistent with Chabi-Yo, Ruenzi, and Weigert (2015). Importantly, the coefficient of CoMove remains highly significant. In specification (3) we control for the lower and upper trail dependencies between stock and market returns (as in Chabi-Yo, Ruenzi, and Weigert (2015)). Systematic tail risk is priced positively on the downside, whereas on the upside stocks with high tail dependence deliver lower returns. Again, the CoMove premium remains high. In Specifications (4) and (5) we control for measures of idiosyncratic risk, in particular idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang (2006)) and last month's maximum and minimum daily return (Bali, Cakici, and Whitelaw (2011)). One could argue that stocks with less frequent co-movement with the market are stocks with higher levels of idiosyncratic risk, so that the premium for CoMove is driven by the idiosyncratic volatility puzzle (Ang, Hodrick, Xing, and Zhang (2006)). As expected, stocks with high idiosyncratic risk and high max returns have predictably lower returns. However, none of these idiosyncratic risk measures explain the premium for CoMove. Last, we analyze whether market liquidity or trading activity can explain the positive association between CoMove and stock returns. Stock returns tend to be higher for illiquid stocks (Amihud (2002)) and after high levels of trading activity (Gervais, Kaniel, and Mingelgrin (2001)), both of which could be related to comovement between stock and market returns. In Specification (6), we add the Amihud (2002) illiquidity ratio as a control variable, and in Specification (7) we control for the level of turnover and changes in turnover over the last two months. Neither illiquidity nor trading activity can explain our main finding: the relation between CoMove and stock returns remains significantly positive.[29]

[29] Results from additional Fama/MacBeth regressions provide further evidence in favor of CoMove being priced, see Table A7 of Internet Appendix A. In these regressions we control for past returns (short- and long-term reversal, in addition to momentum) and the Fama and French (2015) predictors asset growth and profitability. We also include Fama/French-48-industry, NYSE size-decile, and exchange dummie. Last we skip one month between measuring CoMove and predicting stock returns. CoMove always remains a highly

Hence, the premium of high CoMove stock returns over low CoMove stock returns cannot be explained by known determinants of the cross-section of stock returns. Our evidence is in line with investors using a counting heuristic and shying away from buying stocks with a high perceived dependence on market returns.

4 Conclusion

We run several laboratory experiments to analyze how varying dependence between asset returns influences beliefs about dependence and investment decisions. We find that participants consistently adjust their beliefs to changes in linear dependence. They diversify more when correlation decreases, which is in line with Markowitz (1952). Thus, presenting information realistically, using price paths and return series, we do not find correlation neglect. This is in contrast to the previous literature (e.g. Kroll, Levy, and Rapoport (1988)), where information was given in the form of description, with direct statements about probabilities of events, and consistent with new evidence on the effects of presentation formats from Laudenbach, Ungeheuer, and Weber (2016). However, our findings suggest that correlation does not properly capture participants' perception of dependence. When we increase dependence in frequent, moderate returns while decreasing dependence in infrequent, extreme returns, only few participants consistently adjust their beliefs about dependence in extreme returns. In contrast they do understand dependence in frequent, moderate returns. Consequently, they diversify less when dependence in moderate returns increases, even if correlation decreases due to less dependence in extreme returns. This choice is opposite to what one would expect under Markowitz (1952)'s framework. However, it is consistent with results from other experiments on rare events: Hertwig, Barron, Weber, and Erev (2004) find that experience sampling leads to underweighting of rare events. To sum up, differences in dependence are taken into account by participants, but correlation does not properly explain their beliefs and choices, whereas a simple counting heuristic explains our findings. The perception of dependence and investment decisions in the laboratory are driven by the frequency of return comovement, not correlation. Consistent with our experimental evidence, we find that historical stock returns exhibit a return premium for stocks with high frequencies of return comovement with the S&P 500. In particular during the later half of our sample,

significant predictor of stock returns.

between 1989 and 2015 when portfolio and risk management had become broadly discussed topics, we find a strong and robust return premium, with a higher Sharpe Ratio than that of the momentum strategy. Hence, the frequency of return comovement matters, not only for beliefs and investment decisions in the laboratory, but also for historical aggregate market outcomes.

This study has implications for individual investors' portfolio selection. Our findings suggest that investors can improve diversification decisions by debiasing beliefs about dependence in extremes, maybe via viewing information about past returns in a format they better understand. In particular in contexts, where non-linear dependence is large—e.g. structured financial products with embedded options—the neglect of dependence in extreme events may lead to unintentional risk taking. This should be of interest to policy makers, since the financial industry could have an incentive to use investors' neglect of dependence in crashes to unload downside risks via offering structured products with embedded out-of-the money put options. Indeed, Henderson and Pearson (2011) analyze structured equity products and find evidence in line with the 'hypothesis that banks and investment banks design financial products to exploit investors' misunderstandings of financial markets, cognitive biases in evaluating probabilistic information, and framing effects.'

References

Aarbu, K. O., and F. Schroyen, 2014, "Mapping Risk Aversion in Norway Using Hypothetical Income Gambles," Working Paper.

Abdellaoui, M., O. L'Haridon, and C. Paraschiv, 2011, "Experienced vs. Described Uncertainty: Do We Need Two Prospect Theory Specifications?," *Management Science*, 57(10), 1879–1895.

Amihud, Y., 2002, "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects," *Journal of Financial Markets*, 5, 31–56.

Ang, A., J. Chen, and Y. Xing, 2006, "Downside Risk," *The Review of Financial Studies*, 19(4), 1191–1239.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang, 2006, "The Cross-Section of Volatility and Expected Returns," *Journal of FInance*, 61(1), 259–299.

Asparouhova, E., M. Lemmon, and M. Hertzel, 2009, "Inference from Streaks in Random Outcomes: Experimental Evidence on Beliefs in Regime-Shifting and the Law of Small Numbers," *Management Science*, 55(11), 1766–1782.

Bali, T. G., N. Cakici, and R. F. Whitelaw, 2011, "Maxing out: Stocks as lotteries and the cross-section of expected returns," *Journal of Financial Economics*, 99(2), 427–446.

Barberis, N., 2013, "The Psychology of Tail Events: Progress and Challenges," *American Economic Review*, 103(3), 611–616.

Benartzi, S., and R. H. Thaler, 2001, "Naive Diversification Strategies in Defined Contribution Saving Plans," *American Economic Review*, 91(1), 79–98.

Carhart, M. M., 1997, "On Persistence in Mutual Fund Performance," *The Journal of Finance*, 52(March), 57–82.

Chabi-Yo, F., S. Ruenzi, and F. Weigert, 2015, "Crash Sensitivity and the Cross-Section of Expected Stock Returns," Working Paper.

Cohn, A., J. Engelmann, E. Fehr, and M. A. Maréchal, 2015, "Evidence for Countercyclical Risk Aversion: An Experiment with Financial Professionals," *American Economic Review*, 105(2), 860–885.

Cokely, E. T., M. Galesic, E. Schulz, and S. Ghazal, 2012, "Measuring Risk Literacy: The Berlin Numeracy Test," *Judgment and Decision Making*, 7(1), 25–47.

Cornil, Y., and Y. Bart, 2013, "The Diversification Paradox: How Lay Investors Perceive Risk and Covariance Information," *Advances in Consumer Research*, 41, 674–675.

Eyster, E., and G. Weizsäcker, 2011, "Correlation neglect in financial decision-making," Working Paper.

Fama, E. F., and K. R. French, 1992, "The Cross-Section of Expected Stock Returns," *The Journal of Finance*, 47(2), 427–465.

——— , 1993, "Common risk factors in the returns on stocks and bonds," *Journal of Financial Economics*, 33, 3–56.

——— , 2004, "The Capital Asset Pricing Model: Theory and Evidence," *Journal of Economic Perspectives*, 18(3), 25–46.

——— , 2015, "A five-factor asset pricing model," *Journal of Financial Economics*, 116(1), 1–22.

Fama, E. F., and J. D. MacBeth, 1973, "Risk, Return and Equilibrium: Empirical Tests," *Journal of Political Economy*, 81(3), 607–636.

Fernandes, D., J. G. J. Lynch, and R. G. Netemeyer, 2014, "Financial Literacy, Financial Education, and Downstream Financial Behaviors," *Management Science*, 60(8), 1861–1883.

Frazzini, A., and L. H. Pedersen, 2014, "Betting Against Beta," *Journal of Financial Economics*, 111(1), 1–25.

Friend, I., and M. E. Blume, 1975, "The Demand for Risky Assets," *American Economic Review*, 65(5), 900–922.

Gervais, S., R. Kaniel, and D. H. Mingelgrin, 2001, "The High-Volume Return Premium," *Journal of Finance*, 56(3), 877–919.

Glaser, M., T. Langer, J. Reynders, and M. Weber, 2007, "Framing Effects in Stock Market Forecasts: The Difference Between Asking for Prices and Asking for Returns," *Review of Finance*, 11(2), 325–357.

Gubaydullina, Z., and M. Spiwoks, 2009, "Portfolio Diversification: An Experimental Study," Working Paper.

Gul, F., 1991, "A Theory of Disappointment Aversion," *Econometrica*, 59(3), 667–686.

Harvey, C. R., Y. Liu, and H. Zhu, 2016, "...and the Cross-Section of Expected Returns," *Review of Financial Studies*, 29(1), 5–68.

Hedesström, T. M., H. Svedsäter, and T. Gärling, 2006, "Covariation Neglect Among Novice Investors," *Journal of Experimental Psychology: Applied*, 12(3), 155–165.

Henderson, B. J., and N. D. Pearson, 2011, "The dark side of financial innovation: A case study of the pricing of a retail financial product," *Journal of Financial Economics*, 100(2), 227–247.

Hertwig, R., G. Barron, E. U. Weber, and I. Erev, 2004, "Decisions From Experience and the Effect of Rare Events in Risky Choice," *Psychological Science*, 15(8), 534–9.

Hirshleifer, D., and D. Jiang, 2010, "A Financing-Based Misvaluation Factor and the Cross-Section of Expected Returns," *Review of Financial Studies*, 23(9), 3401–3436.

Kahneman, D., and A. Tversky, 1979, "Prospect Theory: An Analysis of Decision under Risk," *Econometrica*, 47(2), 263–292.

Kallir, I., and D. Sonsino, 2009, "The Neglect of Correlation in Allocation Decisions The Neglect of Correlation Allocation Decisions," *Southern Economic Journal*, 75(4), 1045–1066.

Kaufmann, C., M. Weber, and E. Haisley, 2013, "The Role of Experience Sampling and Graphical Displays on One's Investment Risk Appetite," *Management Science*, 59(January 2015), 323–340.

Kelly, B., and H. Jiang, 2014, “Tail Risk and Asset Prices,” *Review of Financial Studies*, 27(10), 2841–2871.

Kimball, M. S., C. R. Sahm, and M. D. Shapiro, 2008, “Imputing Risk Tolerance From Survey Responses,” *Journal of the American Statistical Association*, 103(483), 1028–1038.

Klos, A., and M. Weber, 2006, “Portfolio Choice in the Presence of Non-Tradable Income: An Experimental Analysis,” *German Economic Review*, 7(4), 427–448.

Kroll, Y., and H. Levy, 1992, “Further Tests of the Separation Theorem and the Capital Asset Pricing Model,” *The American Economic Review*, 82(3), 664–670.

Kroll, Y., H. Levy, and A. Rapoport, 1988, “Experimental Tests of the Separation Theorem and the Capital Asset Pricing Model,” *American Economic Review*, 78(3), 500–519.

Laudenbach, C., M. Ungeheuer, and M. Weber, 2016, “How to Overcome Correlation Neglect,” Working Paper.

Markowitz, H. M., 1952, “Portfolio selection,” *The Journal of Finance*, 7(1), 77–91.

Merkle, C., 2016, “The Curious Case of Negative Volatility,” Working Paper.

Metrick, A., 1995, “A natural experiment in ”Jeopardy!”,” *The American Economic Review*, 85(1), 240–253.

Mussweiler, T., and K. Schneller, 2003, “”What Goes Up Must Come Down” - How Charts Influence Decisions to Buy and Sell Stocks,” *Journal of Behavioral Finance*, 4(3), 121–130.

Newey, W. K., and K. D. West, 1987, “A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix,” *Econometrica*, 55(3), 703–708.

Paravisini, D., V. Rappoport, and E. Ravina, 2015, “Risk Aversion and Wealth: Evidence from Person-to-Person Lending Portfolios,” Working Paper.

Pástor, L., and R. F. Stambaugh, 2003, “Risk and Expected Stock Returns,” *Journal of Political Economy*, 111(3), 642–685.

Payzan-LeNestour, E., 2015, “Fooled By Randomness? Financial Decision-Making Under Tail Risk,” Working Paper.

Reinholtz, N., P. M. Fernbach, and B. de Langhe, 2016, "Do People Understand the Benefit of Diversification?," Working Paper.

Roy, A., 1952, "Safety First and the Holding of Assets," *Econometrica*, 20(3), 431–449.

Ruenzi, S., M. Ungeheuer, and F. Weigert, 2016, "Extreme Downside Liquidity Risk," Working Paper.

Sadka, R., 2006, "Momentum and Post-Earnings-Announcement Drift Anomalies: The Role of Liquidity Risk," *Journal of Financial Economics*, 80(2), 309–349.

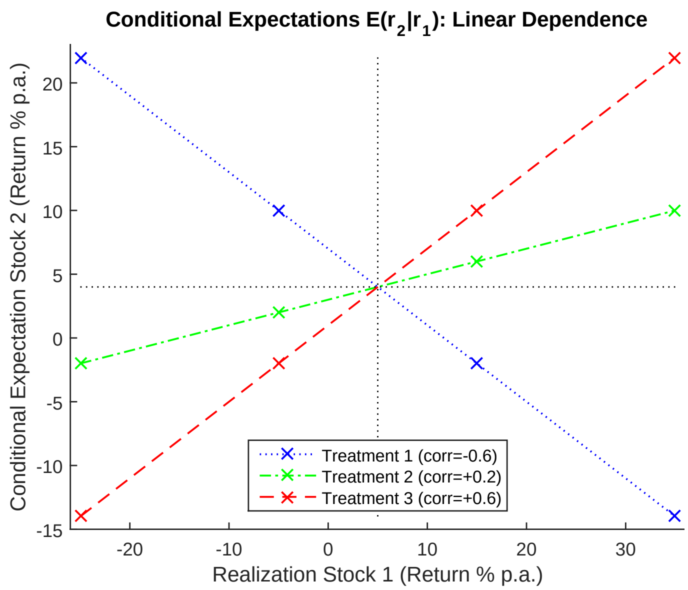
Sharpe, W. F., 1964, "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk," *The Journal of Finance*, 19(3), 425–442.

Tversky, A., and D. Kahneman, 1992, "Advances in Prospect-Theory - Cumulative Representation of Uncertainty," *Journal of Risk and Uncertainty*, 5, 297–323.

Weigert, F., 2016, "Crash Aversion and the Cross-Section of Expected Stock Returns Worldwide," *Review of Asset Pricing Studies*.

Figure 1: Experiment 1 vs. 2: Linear vs. Non-Linear Dependence

These graphs display the expectation for the return of stock 2 conditional on each of the four possible realized returns of stock 1, i.e. $E(r_2|r_1)$. The first graph displays conditional expectations for experiment 1's three treatments. Dependence is linear, i.e. all four conditional expectations are located on one line. The second graph displays conditional expectations for experiment 2's two treatments. Dependence is non-linear. In particular, dependence in moderate returns is opposite to dependence in extreme returns. We also display the expected values for stock 1's (2's) return as the vertical (horizontal) dotted line at 5% (4%).



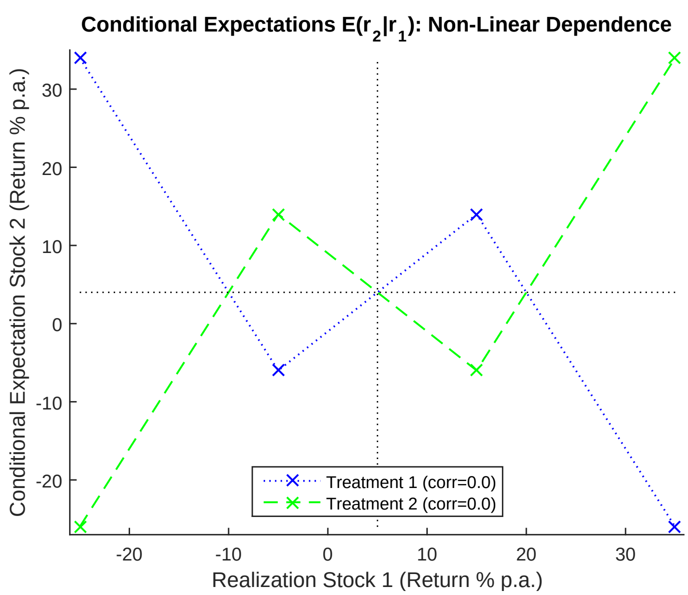


Figure 2: Experiment 1 – Illustrative Price Paths Treatments 1 and 3

These price paths are illustrative examples for the information shown to participants in experiment 1. The first path is an example from treatment 1 (correlation of -0.6) and the second path is from treatment 3 (correlation of +0.6). Returns are displayed in green (red) when positive (negative). The labels are in German. Translations: 'Preis-Simulation für Aktie 1 & 2' means 'Price-Simulation for Stocks 1 & 2'. 'Aktie X (durchschnittliche Rendite pro Jahr = y%)' means 'Stock X (average return per year = y%)'. 'Jahr' and 'Preis' mean 'Year' and 'Price' respectively.

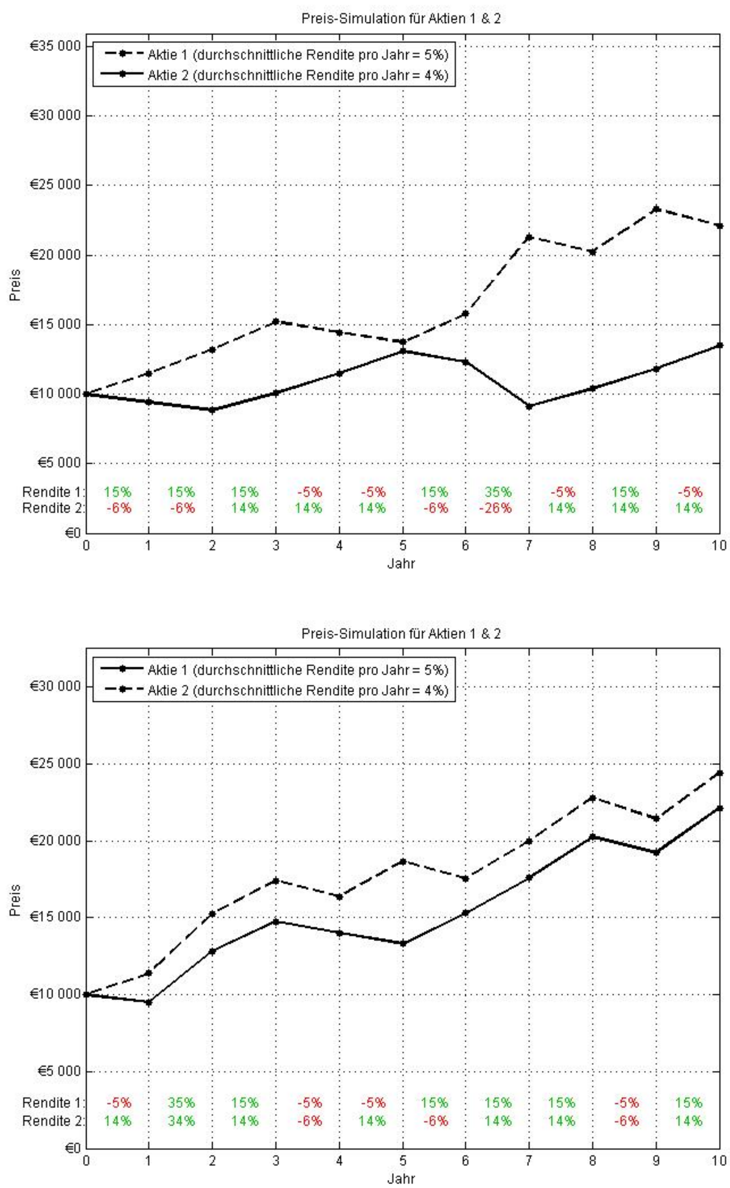


Figure 3: Experiment 1: CRRA-Optimal Investment in Stock 2

For each of the treatments, this figure displays the investment in stock 2 out of $10'000$ € that maximizes the expected CRRA-utility at levels of relative risk aversion between 0.5 and 10. Treatment 1, 2 and 3 exhibit correlations between the two stocks of -0.6, 0.2, and 0.6, respectively. The investment is restricted to be in the closed interval between 0 and 1 and it is assumed that the remaining funds are invested in stock 1.

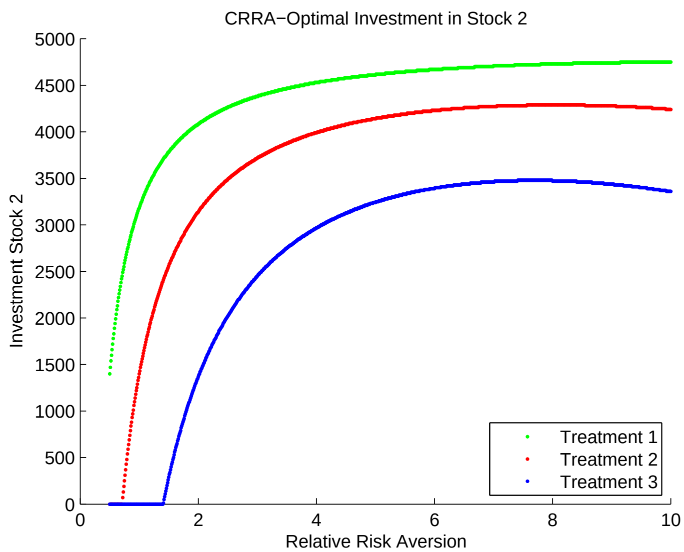


Figure 4: Experiment 2: CRRA-Optimal Investment in Stock 2

For each of the treatments, this figure displays the investment in stock 2 out of 10′000 € that maximizes the expected CRRA-utility at levels of relative risk aversion between 0.5 and 10. Both treatments exhibit zero correlation between the two stocks. Treatment 1 exhibits positive dependence in moderate returns, and negative dependence in extremes. Treatment 2 exhibits negative dependence in moderate returns, and positive dependence in extremes. The investment is restricted to be in the closed interval between 0 and 1 and it is assumed that the remaining funds are invested in stock 1.

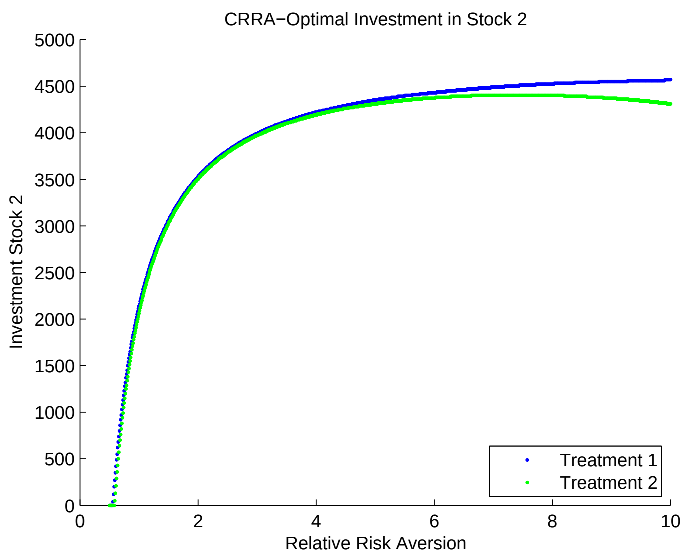


Figure 5: Experiments 3 & 4: CRRA-Optimal Investment in Stock 2

For each of the treatments, this figure displays the investment in stock 2 out of 10′000 € that maximizes the expected CRRA-utility at levels of relative risk aversion between 0.5 and 10. Treatment 1 exhibits a correlation between stock returns of -0.21, positive dependence in moderate returns, and negative dependence in extremes. Treatment 2 exhibits a correlation between stock returns of 0.21, negative dependence in moderate returns, and positive dependence in extremes. The investment is restricted to be in the closed interval between 0 and 1 and it is assumed that the remaining funds are invested in stock 1.

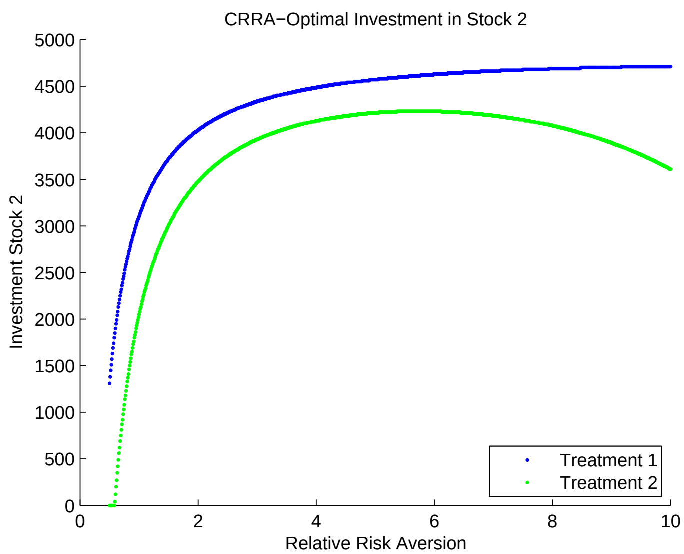
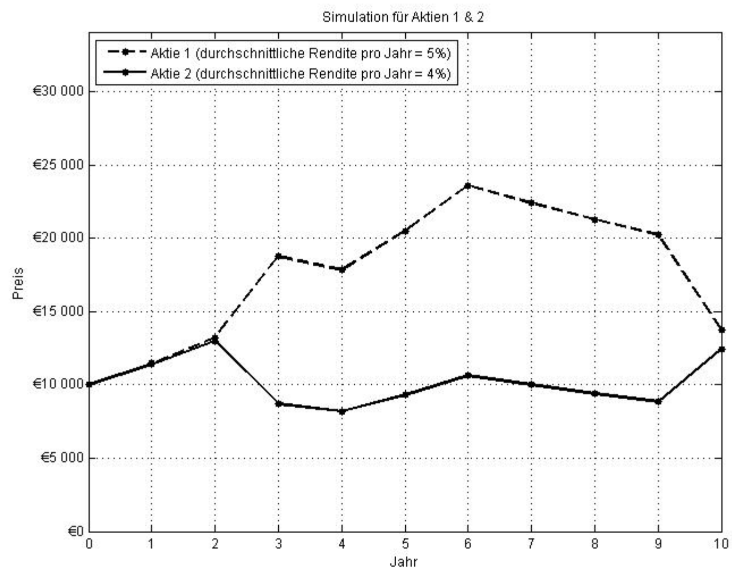


Figure 6: Experiment 4 – Illustrative Price Path Treatments 1 (Price) and 2 (Return)

These price paths and return series are illustrative examples for the information shown to participants in experiment 4. The first path is an example from treatment 1 with price paths (positive dependence in moderate returns, negative in extremes) and the second path is from treatment 2 with return series (negative dependence in moderate returns, positive in extremes). Returns are displayed in green (red) when positive (negative). The labels are in German. Translations: 'Preis-Simulation für Aktie 1 & 2' means 'Price-Simulation for Stocks 1 & 2'. 'Aktie X (durchschnittliche Rendite pro Jahr = y%)' means 'Stock X (average return per year = y%)'. 'Jahr' and 'Preis' mean 'Year' and 'Price' respectively.



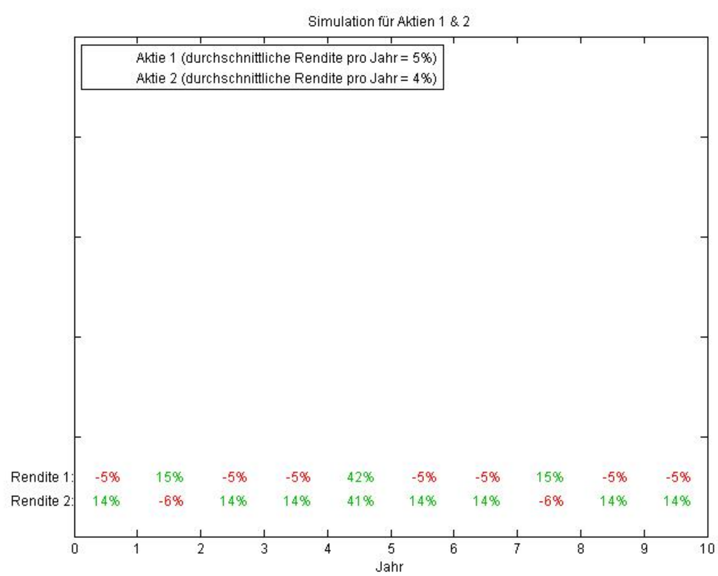


Figure 7: The Pricing of Co-Movement and Beta

In this figure, we display the cumulative Carhart-Alpha of two strategies. High-Minus-Low Comovement is our long-short strategy of buying (selling) stocks, which had the same (opposite) return-sign as the market frequently. High-Minus-Low Beta is a long-short strategy of buying (selling) high (low) market beta stocks. We use quintile portfolios. High-Minus-Low Comovement portfolios are adjusted for Beta via dependent double sorts and High-Minus-Low Beta portfolios are analogously adjusted for Comovement via double sorts, for details see 'Average' portfolio in Panel A of Table 13.

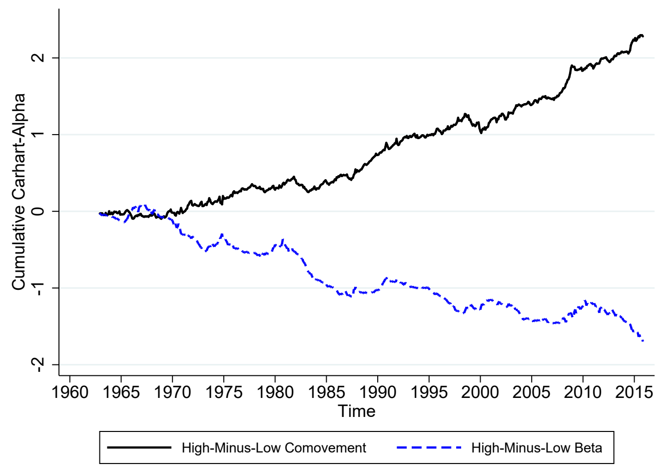


Figure 8: New York Times Articles Related to Risk

In this figure, we display the number of New York Times articles containing words related to risk, normalized by the number of articles containing the word 'stocks'. The words related to risk are: 'correlation', 'volatility', 'risk', 'risk management', and 'portfolio management'. The article numbers are taken directly from the New York Times Chronicle webpage.

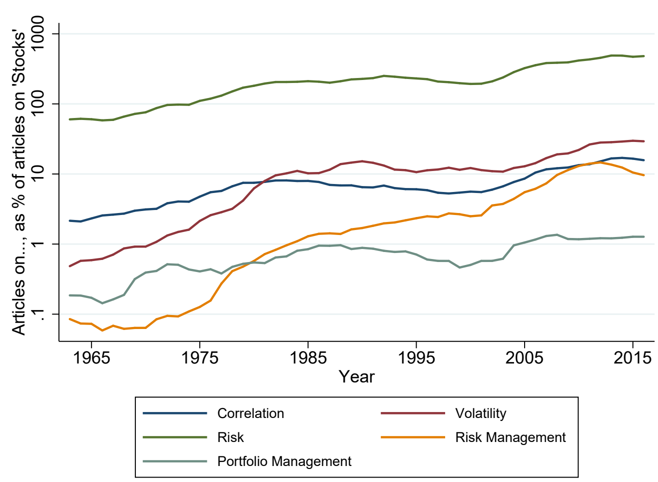


Table 1: Summary Statistics

Numbers in brackets indicate the range of possible values, e.g. values 1-4 for self-assessed knowledge on statistics. Financial literacy is measured as the number of correctly answered questions in the test proposed by Fernandes, Lynch, and Netemeyer (2014). Numeracy is measured as the number of correctly answered questions in the test proposed by Cokely, Galesic, Schulz, and Ghazal (2012).

	Mean	Std.Dev.	10%ile	50%ile	90%ile
	Panel A: Experiment 1 (127 participants)				
Age	21.87	4.31	18	21	26
Fraction Male	0.55	0.50	0	1	1
Owns Stocks or Equity Funds	0.20	0.40	0	0	1
Interested in Financial Markets	0.69	0.47	0	1	1
Willingness to Take Risks (1-5)	2.87	1.15	1	3	4
Has Taken Statistics Course	0.36	0.48	0	0	1
Statistics Knowledge (1-4)	2.83	0.96	1	3	4
Financial Literacy (0-12)	8.31	2.71	5	9	11
Numeracy (0-4)	1.89	1.25	0	2	4
	Panel B: Experiment 2 (94 participants)				
Age	24.10	5.14	19	23	30
Fraction Male	0.43	0.50	0	0	1
Owns Stocks or Equity Funds	0.21	0.41	0	0	1
Interested in Financial Markets	0.59	0.50	0	1	1
Willingness to Take Risks (1-5)	2.51	1.14	1	2	4
Has Taken Statistics Course	0.63	0.49	0	1	1
Statistics Knowledge (1-4)	2.68	1.04	1	3	4
Financial Literacy (0-12)	7.85	2.98	3	8	11
Numeracy (0-4)	1.97	1.28	0	2	4
	Panel C: Experiment 3 (107 participants)				
Age	22.32	3.83	19	21	26
Fraction Male	0.47	0.50	0	0	1
Owns Stocks or Equity Funds	0.15	0.36	0	0	1
Interested in Financial Markets	0.56	0.50	0	1	1
Willingness to Take Risks (1-5)	2.61	1.01	1	2	4
Has Taken Statistics Course	0.78	0.42	0	1	1
Statistics Knowledge (1-4)	2.60	0.92	1	3	4
Financial Literacy (0-12)	8.38	2.59	5	9	11
Numeracy (0-4)	2.33	1.28	1	2	4
	Panel D: Experiment 4 (138 participants)				
Age	23.65	6.53	19	22	29
Fraction Male	0.59	0.49	0	1	1
Owns Stocks or Equity Funds	0.25	0.44	0	0	1
Interested in Financial Markets	0.63	0.48	0	1	1
Willingness to Take Risks (1-5)	2.80	1.13	1	3	4
Has Taken Statistics Course	0.56	0.50	0	1	1
Statistics Knowledge (1-4)	2.62	1.08	1	3	4
Financial Literacy (0-12)	8.49	2.64	5	9	12
Numeracy (0-4)	2.20	1.31	0	2	4

Table 2: Experiment 1 – Treatments: Probability Distributions

Tables show the joint distribution for stock 1 (returns in first row) and stock 2 (returns in first column) for all treatments. Marginal distributions are kept constant across treatments and experiments. Means are 5.0% for stock 1 and 4.0% for stock 2. Standard-deviations are 13.0% for both stocks. In experiment 1 correlation varies across treatments and dependence is linear.

Treatment 1: Pearson-Correlation of −0.6

return	−25%	−5%	15%	35%	sum
−26%	1%	0%	0%	4%	5%
−6%	0%	9%	36%	0%	45%
14%	0%	36%	9%	0%	45%
34%	4%	0%	0%	1%	5%
sum	5%	45%	45%	5%	100%

Treatment 2: Pearson-Correlation of +0.2

return	−25%	−5%	15%	35%	sum
−26%	3%	0%	0%	2%	5%
−6%	0%	27%	18%	0%	45%
14%	0%	18%	27%	0%	45%
34%	2%	0%	0%	3%	5%
sum	5%	45%	45%	5%	100%

Treatment 3: Pearson-Correlation of +0.6

return	−25%	−5%	15%	35%	sum
−26%	4%	0%	0%	1%	5%
−6%	0%	36%	9%	0%	45%
14%	0%	9%	36%	0%	45%
34%	1%	0%	0%	4%	5%
sum	5%	45%	45%	5%	100%

Table 3: Experiment 1 – Perception of Dependence

The panels show the frequency of each answer-category for questions on beliefs about dependence. Boxes around numbers indicate correct answers (based on data shown to participants; panel A does not have one correct answer). Below panels A, C and D, you will find the mean category for each treatment and differences between these means. Below panel B you will find mean probability estimates and differences between these mean estimates. Standard errors are in brackets. 1/2/3 stars denote significance at the 10/5/1%-level.

	Treatment 1 Correlation=-0.6	Treatment 2 Correlation=+0.2	Treatment 3 Correlation=+0.6
Panel A (Overall Dependence): Stocks 1 and 2 move...			
in opposite directions 1	$\boxed{13}$	1	0
2	$\boxed{81}$	14	7
3	26	$\boxed{46}$	22
4	6	$\boxed{64}$	$\boxed{80}$
together 5	1	2	$\boxed{18}$
mean	2.22	3.41	3.86
-Treatment 1	-	1.19^{***} (0.09)	1.64^{***} (0.09)
-Treatment 2	-	-	0.45^{***} (0.09)
Panel B1 (Frequency of Co-Movement): Given stock 1's price decreases, I expect stock 2's price to increase in ... out of 100 cases. (Any answer from 0 to 100 was allowed.)			
[0,20)	3	12	45
20	1	21	$\boxed{25}$
(20,40)	3	26	14
40	8	$\boxed{15}$	10
(40,60)	23	20	9
60	15	12	5
(60,80)	30	11	8
80	$\boxed{27}$	7	8
(80,100]	17	3	3
mean	65.36	41.59	31.45
-Treatment 1	-	-23.77^{***} (2.69)	-33.91^{***} (2.69)
-Treatment 2	-	-	-10.14^{***} (2.69)
Panel B2 (Frequency of Co-Movement): Given stock 1's price increases, I expect stock 2's price to increase in ... out of 100 cases. (Any answer from 0 to 100 was allowed.)			
[0,20)	25	5	6
20	$\boxed{19}$	7	4
(20,40)	24	15	2
40	10	8	9
(40,60)	19	22	11
60	8	$\boxed{18}$	7
(60,80)	11	26	21
80	4	17	$\boxed{35}$
(80,100]	7	9	32
mean	38.48	56.12	68.41
-Treatment 1	-	17.64^{***} (2.84)	29.93^{***} (2.84)
-Treatment 2	-	-	12.29^{***} (2.84)

	Treatment 1 Correlation=-0.6	Treatment 2 Correlation=+0.2	Treatment 3 Correlation=+0.6
Panel C1 (Extreme Dependence): Given that stock 1's price decreases strongly (by more than 20%), I expect stock 2 to...			
decrease 1	9	46	82
2	15	36	22
increase 3	103	45	23
mean	2.74	1.99	1.54
-Treatment 1	-	-0.75*** (0.09)	-1.20*** (0.09)
-Treatment 2	-	-	-0.45*** (0.09)
Panel C2 (Extreme Dependence): Given that stock 1's price increases strongly (by more than 20%), I expect stock 2 to...			
decrease 1	91	41	23
2	26	40	25
increase 3	10	46	79
mean	1.36	2.04	2.44
-Treatment 1	-	0.68*** (0.09)	1.08*** (0.09)
-Treatment 2	-	-	0.40*** (0.09)
Panel D1 (Moderate Dependence): Given that stock 1's price decreases moderately (by less than 20%), I expect stock 2 to...			
decrease 1	16	49	68
2	66	63	47
increase 3	45	15	12
mean	2.23	1.73	1.56
-Treatment 1	-	-0.50*** (0.08)	-0.67*** (0.08)
-Treatment 2	-	-	-0.17** (0.08)
Panel D2 (Moderate Dependence): Given that stock 1's price increases moderately (by less than 20%), I expect stock 2 to...			
decrease 1	48	16	7
2	64	42	50
increase 3	15	49	70
mean	1.74	2.26	2.50
-Treatment 1	-	0.52*** (0.08)	0.76*** (0.08)
-Treatment 2	-	-	0.24*** (0.08)

Table 4: Experiment 1 – Investment Decision

Inv_2 is the investment in stock 2. I_{ti} is a dummy for treatment i. The subscript N denotes normalization to a mean of zero and standard deviation of one. RA is self-assessed riskaversion ($= -1\times$ willingness to take risk). FL is the financial literacy score according to Fernandes, Lynch, and Netemeyer (2014). NUM is the numeracy score according to Cokely, Galesic, Schulz, and Ghazal (2012). We run random effects regressions to take account of participant-specific effects. Since the treatment is orthogonal to participant characteristics, random effects—as opposed to fixed effects—regressions are justified. This is also why adding control variables does not change treatment effect estimates. Treatments 1, 2, and 3 exhibit correlations between stock returns of -0.6, 0.2, and 0.6, respectively. Standard-errors are reported in brackets. 1/2/3 stars denote significance at the 10/5/1%-level.

	Inv_2 (1)	Inv_2 (2)	Inv_2 (3)	Inv_2 (4)
Constant	3186.31***	3186.31***	3186.31***	3186.31***
	(171.57)	(165.93)	(163.90)	(164.09)
I_{t1}	926.02***	926.02***	926.02***	926.02***
	(212.28)	(212.28)	(212.28)	(212.72)
I_{t2}	707.00***	707.00***	707.00***	707.00***
	(212.28)	(212.28)	(212.28)	(212.72)
RA_N		503.25***	425.77***	425.77***
		(112.00)	(112.32)	(112.32)
FL_N			-268.91**	-292.94
			(121.04)	(181.83)
NUM_N			-118.99	-284.62
			(121.61)	(182.21)
FL_N*I_{t1}				138.02
				(235.03)
FL_N*I_{t2}				-65.93
				(235.03)
NUM_N*I_{t1}				244.50
				(235.03)
NUM_N*I_{t2}				252.40
				(235.03)
Random Effects	YES	YES	YES	YES
No. obs.	381	381	381	381

Table 5: Experiment 2 – Treatments: Probability Distributions

Tables show the joint distribution for stock 1 (returns in first row) and stock 2 (returns in first column) for all treatments. Marginal distributions are kept constant across treatments and experiments. Means are 5.0% for stock 1 and 4.0% for stock 2. Standard-deviations are 13.0% for both stocks. In experiment 2 correlation is kept at zero and non-linear dependence in extreme vs. moderate returns is varied. Treatment 1 exhibits negative dependence in extreme returns and positive dependence in moderate returns. Treatment 2 exhibits positive dependence in extreme returns and negative dependence in moderate returns.

Treatment 1: Pearson-Correlation of 0.0

return	−25%	−5%	15%	35%	sum
−26%	0%	0%	0%	5%	5%
−6%	0%	45%	0%	0%	45%
14%	0%	0%	45%	0%	45%
34%	5%	0%	0%	0%	5%
sum	5%	45%	45%	5%	100%

Treatment 2: Pearson-Correlation of 0.0

return	−25%	−5%	15%	35%	sum
−26%	5%	0%	0%	0%	5%
−6%	0%	0%	45%	0%	45%
14%	0%	45%	0%	0%	45%
34%	0%	0%	0%	5%	5%
sum	5%	45%	45%	5%	100%

Table 6: Experiment 2 – Perception of Dependence

The panels show the frequency of each answer-category for questions on beliefs about dependence. Boxes around numbers indicate correct answers (based on data shown to participants; panel A does not have one correct answer). Treatment 1 exhibits negative dependence in extreme returns and positive dependence in moderate returns. Treatment 2 exhibits positive dependence in extreme returns and negative dependence in moderate returns. Below panels A, C and D, you will find the mean category for each treatment and differences between these means. Below panel B you will find mean probability estimates and differences between these mean estimates. Standard errors are in brackets. 1/2/3 stars denote significance at the 10/5/1%-level.

	Treatment 1	Treatment 2
Panel A (Overall Dependence): Stocks 1 and 2 move...		
in opposite directions 1	1	7
2	5	43
3	31	24
4	55	18
together 5	2	2
mean	3.55	2.63
-Treatment 1	-	-0.93*** (0.12)
Panel B1 (Frequency of Co-Movement): Given stock 1's price decreases, I expect stock 2's price to increase in ... out of 100 cases. (Any answer from 0 to 100 was allowed.)		
[0,10)	8	3
10	$\boxed{10}$	0
(10,50)	42	20
50	11	12
(50,90)	18	40
90	2	$\boxed{14}$
(90,100]	3	3
mean	38.00	62.83
-Treatment 1	-	24.83*** (3.76)
Panel B2 (Frequency of Co-Movement): Given stock 1's price increases, I expect stock 2's price to increase in ... out of 100 cases. (Any answer from 0 to 100 was allowed.)		
[0,10)	4	10
10	4	$\boxed{12}$
(10,50)	12	30
50	16	15
(50,90)	42	23
90	$\boxed{9}$	2
(90,100]	7	2
mean	62.12	40.69
-Treatment 1	-	-21.43*** (3.85)

	Treatment 1	Treatment 2
Panel C1 (Extreme Dependence): Given that stock 1's price decreases strongly (by more than 20%), I expect stock 2 to...		
decrease 1	26	$\boxed{31}$
2	27	22
increase 3	$\boxed{41}$	41
mean	2.16	2.11
-Treatment 1	-	-0.05 (0.12)
Panel C2 (Extreme Dependence): Given that stock 1's price increases strongly (by more than 20%), I expect stock 2 to...		
decrease 1	$\boxed{37}$	41
2	27	24
increase 3	30	$\boxed{29}$
mean	1.93	1.87
-Treatment 1	-	-0.05 (0.12)
Panel D1 (Moderate Dependence): Given that stock 1's price decreases moderately (by less than 20%), I expect stock 2 to...		
decrease 1	$\boxed{48}$	8
2	36	41
increase 3	10	$\boxed{45}$
mean	1.60	2.39
-Treatment 1	-	0.80^{***} (0.10)
Panel D2 (Moderate Dependence): Given that stock 1's price increases moderately (by less than 20%), I expect stock 2 to...		
decrease 1	9	$\boxed{41}$
2	34	37
increase 3	$\boxed{51}$	16
mean	2.45	1.73
-Treatment 1	-	-0.71^{***} (0.10)

Table 7: Experiment 2 – Investment Decision

Inv_2 is the investment in stock 2. I_{ti} is a dummy for treatment i. Treatment 1 exhibits negative dependence in extreme returns and positive dependence in moderate returns. Treatment 2 exhibits positive dependence in extreme returns and negative dependence in moderate returns. I_c is a dummy, which is 1 for type 3 subjects, i.e. subjects that get ≥ 3 out of 4 questions about extreme dependence right. The subscript N denotes normalization to a mean of zero and standard deviation of one. FL is the financial literacy score according to Fernandes, Lynch, and Netemeyer (2014). NUM is the numeracy score according to Cokely, Galesic, Schulz, and Ghazal (2012). We run random effects regressions to take account of participant-specific effects. Since the treatment is orthogonal to participant characteristics, random effects—as opposed to fixed effects—regressions are justified. This is also why adding control variables does not change treatment effect estimates. Standard errors are reported in brackets. 1/2/3 stars denote significance at the 10/5/1%-level.

	Inv_2 All Types (1)	Inv_2 Types 1 & 2 (2)	Inv_2 Type 3 (3)	Inv_2 Types 1 & 2 (4)
Constant	3618.77***	3618.77***	3531.25***	3618.77***
	(212.09)	(212.10)	(468.19)	(213.20)
I_{t2}	560.72**	560.72*	-512.50	560.72*
	(279.50)	(295.55)	(386.96)	(298.00)
I_{t2}*I_c	-1073.22			
	(677.45)			
I_c	-87.52			
	(514.08)			
FL_N				-210.56
				(248.44)
NUM_N				53.67
				(248.44)
FL_N*I_{t2}				161.88
				(347.25)
NUM_N*I_{t2}				-298.73
				(347.25)
Random Effects	YES	YES	YES	YES
No. obs.	188	156	32	156

Table 8: Experiments 3 & 4 – Treatments: Probability Distributions

Tables show the joint distribution for stock 1 (returns in first row) and stock 2 (returns in first column) for all treatments. Marginal distributions are kept constant across treatments and experiments. Means are 5.0% for stock 1 and 4.0% for stock 2. Standard-deviations are 15.14% for both stocks. In experiments 3 and 4 correlation and dependence in extreme returns increase, while dependence in moderate returns decreases from treatment 1 to treatment 2. Treatment 1 exhibits a correlation between stock returns of -0.21, negative dependence in extreme returns and positive dependence in moderate returns. Treatment 2 exhibits a correlation between stock returns of +0.21, positive dependence in extreme returns and negative dependence in moderate returns.

Treatment 1: Pearson-Correlation of −0.21

return	−32%	−5%	15%	42%	sum
−33%	0%	0%	0%	5%	5%
−6%	0%	45%	0%	0%	45%
14%	0%	0%	45%	0%	45%
41%	5%	0%	0%	0%	5%
sum	5%	45%	45%	5%	100%

Treatment 2: Pearson-Correlation of +0.21

return	−32%	−5%	15%	42%	sum
−33%	5%	0%	0%	0%	5%
−6%	0%	0%	45%	0%	45%
14%	0%	45%	0%	0%	45%
41%	0%	0%	0%	5%	5%
sum	5%	45%	45%	5%	100%

Table 9: Experiment 3 – Perception of Dependence

The panels show the frequency of each answer-category for questions on beliefs about dependence. Boxes around numbers indicate correct answers (based on data shown to participants; panel A does not have one correct answer). Treatment 1 exhibits negative correlation, negative dependence in extreme returns and positive dependence in moderate returns. Treatment 2 exhibits positive correlation, positive dependence in extreme returns and negative dependence in moderate returns. Below panels A, C and D, you will find the mean category for each treatment and differences between these means. Below panel B you will find mean probability estimates and differences between these mean estimates. Standard errors are in brackets. 1/2/3 stars denote significance at the 10/5/1%-level.

	Treatment 1	Treatment 2
Panel A (Overall Dependence): Stocks 1 and 2 move...		
in opposite directions 1	0	3
2	16	56
3	36	27
4	52	20
together 5	3	1
mean	3.39	2.63
-Treatment 1	-	-0.77*** (0.11)
Panel B1 (Frequency of Co-Movement): Given stock 1's price decreases, I expect stock 2's price to increase in ... out of 100 cases. (Any answer from 0 to 100 was allowed.)		
[0,10)	10	1
10	$\boxed{6}$	1
(10,50)	50	29
50	14	12
(50,90)	25	53
90	2	$\boxed{9}$
(90,100]	0	2
mean	38.58	59.35
-Treatment 1	-	20.77*** (3.25)
Panel B2 (Frequency of Co-Movement): Given stock 1's price increases, I expect stock 2's price to increase in ... out of 100 cases. (Any answer from 0 to 100 was allowed.)		
[0,10)	2	5
10	2	$\boxed{7}$
(10,50)	22	45
50	13	16
(50,90)	56	29
90	$\boxed{6}$	4
(90,100]	6	1
mean	60.58	43.98
-Treatment 1	-	-16.60*** (3.27)

	Treatment 1	Treatment 2
Panel C1 (Extreme Dependence): Given that stock 1's price decreases strongly (by more than 20%), I expect stock 2 to...		
decrease 1	26	$\boxed{34}$
2	24	31
increase 3	$\boxed{57}$	42
mean	2.29	2.07
-Treatment 1	-	-0.21* (0.11)
Panel C2 (Extreme Dependence): Given that stock 1's price increases strongly (by more than 20%), I expect stock 2 to...		
decrease 1	$\boxed{48}$	41
2	28	28
increase 3	31	$\boxed{38}$
mean	1.84	1.97
-Treatment 1	-	0.13 (0.12)
Panel D1 (Moderate Dependence): Given that stock 1's price decreases moderately (by less than 20%), I expect stock 2 to...		
decrease 1	$\boxed{58}$	8
2	41	43
increase 3	8	$\boxed{56}$
mean	1.53	2.45
-Treatment 1	-	0.92*** (0.09)
Panel D2 (Moderate Dependence): Given that stock 1's price increases moderately (by less than 20%), I expect stock 2 to...		
decrease 1	10	$\boxed{52}$
2	43	47
increase 3	$\boxed{54}$	8
mean	2.41	1.59
-Treatment 1	-	-0.82*** (0.09)

Table 10: Experiment 3 – Investment Decision

Inv_2 is the investment in stock 2. I_{ti} is a dummy for treatment i. Treatment 1 exhibits negative correlation, negative dependence in extreme returns and positive dependence in moderate returns. Treatment 2 exhibits positive correlation, positive dependence in extreme returns and negative dependence in moderate returns. I_c is a dummy, which is 1 for type 3 subjects, i.e. subjects that get ≥ 3 out of 4 questions about extreme dependence right. The subscript N denotes normalization to a mean of zero and standard deviation of one. FL is the financial literacy score according to Fernandes, Lynch, and Netemeyer (2014). NUM is the numeracy score according to Cokely, Galesic, Schulz, and Ghazal (2012). We run random effects regressions to take account of participant-specific effects. Since the treatment is orthogonal to participant characteristics, random effects—as opposed to fixed effects—regressions are justified. This is also why adding control variables does not change treatment effect estimates. Standard errors are reported in brackets. 1/2/3 stars denote significance at the 10/5/1%-level.

	Inv_2 All Types (1)	Inv_2 Types 1 & 2 (2)	Inv_2 Type 3 (3)	Inv_2 Types 1 & 2 (4)
Constant	3154.42***	3154.42***	3250.00***	3154.42***
	(192.56)	(199.66)	(321.51)	(197.12)
I_{t2}	923.02***	923.02***	952.38**	923.02***
	(259.41)	(273.30)	(383.15)	(275.49)
$I_{t2}*I_c$	29.36			
	(585.56)			
I_c	95.58			
	(434.66)			
FL_N				-271.80
				(241.32)
NUM_N				-293.26
				(241.32)
FL_N*I_{t2}				140.65
				(337.27)
NUM_N*I_{t2}				111.32
				(337.27)
Random Effects	YES	YES	YES	YES
No. obs.	214	172	42	172

Table 11: Experiment 4 – Perception of Dependence

The panels show the frequency of each answer-category for questions on beliefs about dependence. Boxes around numbers indicate correct answers (based on data shown to participants; panel A does not have one correct answer). Treatment 1 exhibits negative correlation, negative dependence in extreme returns and positive dependence in moderate returns. Treatment 2 exhibits positive correlation, positive dependence in extreme returns and negative dependence in moderate returns. Below panels A, C and D, you will find the mean category for each treatment and differences between these means. Below panel B you will find mean probability estimates and differences between these mean estimates. Standard errors are in brackets. 1/2/3 stars denote significance at the 10/5/1%-level.

	Return Group		Price Group	
	1	2	1	2
Panel A (Overall Dependence): Stocks 1 and 2 move...				
in opposite directions 1	0	2	1	6
2	3	42	4	34
3	12	13	25	18
4	41	5	46	18
together 5	6	0	0	0
mean	3.81	2.34	3.53	2.63
-Treatment 1	-	-1.47*** (0.12)	-	-0.89*** (0.13)
Panel B1 (Frequency of Co-Movement): Given stock 1's price decreases, I expect stock 2's price to increase in ... out of 100 cases. (Any answer from 0 to 100 was allowed.)				
[0,10)	6	0	3	2
10	$\boxed{12}$	1	$\boxed{6}$	3
(10,50)	27	6	43	23
50	3	8	11	11
(50,90)	12	31	12	28
90	2	$\boxed{9}$	1	$\boxed{7}$
(90,100]	0	7	0	2
mean	32.76	70.29	33.86	53.54
-Treatment 1	-	37.53*** (4.35)	-	19.68*** (3.83)
Panel B2 (Frequency of Co-Movement): Given stock 1's price increases, I expect stock 2's price to increase in ... out of 100 cases. (Any answer from 0 to 100 was allowed.)				
[0,10)	2	7	0	3
10	0	$\boxed{6}$	0	$\boxed{5}$
(10,50)	14	18	20	25
50	4	8	12	15
(50,90)	27	17	37	24
90	$\boxed{12}$	4	$\boxed{7}$	4
(90,100]	3	2	0	0
mean	65.53	44.40	59.16	46.95
-Treatment 1	-	-21.13*** (5.09)	-	-12.21*** (3.90)

	Return Group		Price Group	
	1	2	1	2
Panel C1 (Extreme Dependence): Given that stock 1's price decreases strongly (by more than 20%), I expect stock 2 to...				
decrease 1	15	$\boxed{36}$	17	$\boxed{19}$
2	9	8	20	19
increase 3	$\boxed{38}$	18	$\boxed{39}$	38
mean	2.37	1.71	2.29	2.25
-Treatment 1	-	-0.66*** (0.16)	-	-0.04 (0.13)
Panel C2 (Extreme Dependence): Given that stock 1's price increases strongly (by more than 20%), I expect stock 2 to...				
decrease 1	$\boxed{38}$	17	$\boxed{32}$	37
2	8	11	19	20
increase 3	16	$\boxed{34}$	25	$\boxed{19}$
mean	1.65	2.27	1.91	1.76
-Treatment 1	-	0.63*** (0.16)	-	-0.14 (0.14)
Panel D1 (Moderate Dependence): Given that stock 1's price decreases moderately (by less than 20%), I expect stock 2 to...				
decrease 1	$\boxed{44}$	5	$\boxed{37}$	10
2	16	18	32	31
increase 3	2	$\boxed{39}$	7	$\boxed{35}$
mean	1.32	2.55	1.61	2.33
-Treatment 1	-	1.23*** (0.11)	-	0.72*** (0.11)
Panel D2 (Moderate Dependence): Given that stock 1's price increases moderately (by less than 20%), I expect stock 2 to...				
decrease 1	4	$\boxed{37}$	5	$\boxed{33}$
2	12	16	32	30
increase 3	$\boxed{46}$	9	$\boxed{39}$	13
mean	2.68	1.55	2.45	1.74
-Treatment 1	-	-1.13*** (0.12)	-	-0.71*** (0.11)

Table 12: Experiment 4 – Investment Decision

Inv_2 is the investment in stock 2. I_{ti} is a dummy for treatment i. Treatment 1 exhibits negative correlation, negative dependence in extreme returns and positive dependence in moderate returns. Treatment 2 exhibits positive correlation, positive dependence in extreme returns and negative dependence in moderate returns. I_p is a dummy, which is 1 for price treatments, i.e. the subjects that are shown price paths (not return series). Since the treatment is orthogonal to participant characteristics, random effects—as opposed to fixed effects—regressions are justified. This is also why adding control variables would not change treatment effect estimates. Standard errors are reported in brackets. 1/2/3 stars denote significance at the 10/5/1%-level.

	Return Group		Price Group		Both Groups
	Inv_2	Inv_2	Inv_2	Inv_2	Inv_2
	Types 1 & 2	Type 3	Types 1 & 2	Type 3	All Types
	(1)	(2)	(3)	(4)	(5)
Constant	3373.53***	2881.93***	4533.33***	3154.42***	3151.52***
	(363.60)	(343.55)	(482.39)	(197.12)	(244.34)
I_{t2}	823.71**	1049.39***	293.28	-1527.46**	925.6***
	(350.20)	(374.44)	(286.90)	(647.89)	(282.66)
I_{t2}*I_p					-991.71***
					(380.89)
I_p					545.19*
					(329.25)
Random Effects	YES	YES	YES	YES	YES
No. obs.	68	56	122	30	276

Table 13: Portfolio Sorts and Factor Models

Panel A: Sort by Frequency of Co-Movement, Controlling for β						
	1963-2015		1963-1988		1989-2015	
	Raw	4F-α	Raw	4F-α	Raw	4F-α
			1963-2015			
Low CoMove	0.60%	-0.21%***	0.78%	-0.10%	0.42%	-0.27%**
2	0.73%	-0.02%	0.77%	-0.02%	0.69%	0.02%
3	0.74%	0.02%	0.76%	0.02%	0.71%	0.06%
4	0.81%	0.09%	0.81%	0.09%*	0.82%	0.16%**
High CoMove	0.83%	0.15%**	0.77%	0.13%**	0.89%	0.23%***
High-Low	0.23%**	0.36%***	-0.01%	0.24%**	0.46%***	0.51%***
annualized	2.76%**	4.30%***	-0.12%	2.83%**	5.53%***	6.08%***
	(2.32)	(4.20)	(-0.07)	(2.01)	(3.17)	(3.94)

Panel B: Other Factor Models (annualized α)				
	1963-2015	1963-1988	1989-2015	Available
Raw	2.76%**	-0.12%	5.53%***	1963-
	(2.32)	(-0.07)	(3.17)	2015
1F	2.73%**	-0.13%	5.51%***	1963-
	(2.26)	(-0.08)	(3.05)	2015
3F	3.78%***	1.65%	5.86%***	1963-
	(3.78)	(1.18)	(4.00)	2015
4F	4.30%***	2.83%**	6.08%***	1963-
	(4.20)	(2.01)	(3.94)	2015
4F + ST + LT	4.41%***	2.19%	6.23%***	1963-
	(4.23)	(1.51)	(4.05)	2015
4F + BAB	4.77%***	3.53%**	6.95%***	1963-
	(4.54)	(2.45)	(4.45)	2015
4F + Kelly	4.69%***	3.16%*	5.91%***	1973-
	(3.93)	(1.71)	(3.71)	11/2013
4F + PS	4.33%***	2.85%*	5.80%***	1968-
	(3.89)	(1.80)	(3.69)	2015
4F + Sadka	6.00%***	9.90%***	5.85%***	4/1983-
	(4.34)	(4.07)	(3.60)	2012
4F + UMO	6.04%***	6.45%***	7.09%***	7/1972-
	(5.01)	(3.56)	(4.34)	2014
FF-5F	3.23%***	0.94%	4.41%***	7/1963-
	(3.39)	(0.65)	(3.03)	2015

In this table, we report sorts by the frequency of comovement incl. long-short returns and their Carhart-alphas (Panel A, controlling for beta via a dependent double sort), as well as alphas from other factor models (Panel B). Frequency of comovement is measured as the frequency of equally signed stock and market (S&P 500) returns over the last 36 months. (1F) stands for the 1-factor model with market returns. (3F) stands for the 3-factor model with market, size, and value factor. (4F) stands for the 4-factor model extending (3F) by the momentum factor. For definitions of all factors, see Internet Appendix C. All results are reported for equal-weighted portfolios. The sample covers all $\geq$ \$1 U.S. common stocks traded on the NYSE and AMEX from 1963 to 2015 (Panel A, in Panel B factors are sometimes available only for a subperiod). t-statistics are based on Newey and West (1987) standard errors with one lag and are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 14: Fama/MacBeth Regressions: Controlling for Other Measures of Dependence and Volatility

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CoMove	0.0118***	0.0116***	0.0105***	0.0065***	0.0072***	0.0112***	0.0113***
	(4.78)	(4.72)	(4.11)	(2.83)	(3.16)	(4.64)	(4.67)
β	-0.0016		-0.0012	0.0008	0.0015	-0.0018	-0.0012
	(-1.02)		(-0.77)	(0.59)	(1.05)	(-1.17)	(-0.80)
ln(Size)	-0.0006	-0.0006	-0.0006	-0.0016***	-0.0015***	-0.0010*	-0.0007*
	(-1.40)	(-1.46)	(-1.40)	(-4.53)	(-4.13)	(-1.86)	(-1.75)
ln(B/M)	0.0028***	0.0028***	0.0032***	0.0026***	0.0025***	0.0028***	0.0028***
	(5.62)	(5.53)	(6.00)	(5.30)	(5.02)	(5.56)	(5.63)
$\text{Ret}_{\text{t-12,t-2}}$	0.0096***	0.0097***	0.0098***	0.0088***	0.0088***	0.0096***	0.0102***
	(7.00)	(7.20)	(6.99)	(6.52)	(6.42)	(7.08)	(7.38)
β^-		-0.0010					
		(-0.91)					
β^+		-0.0005					
		(-0.72)					
LTD			0.0156***				
			(3.76)				
UTD			-0.0159***				
			(-3.51)				
Idio. Vola.				-0.3339***			
				(-10.19)			
Min					0.0063		
					(0.48)		
Max					-0.1238***		
					(-14.81)		
Amihud						-0.0003	
						(-0.90)	
ln(turn.)							-0.0006
							(-1.58)
Δ ln(turn.)							0.0029***
							(6.47)
Average R^2	5.82%	6.06%	6.32%	6.37%	6.59%	6.11%	6.38%
Average N	1718	1718	1703	1717	1717	1717	1715
T	636	636	600	636	636	636	636

In this table, we report results from Fama and MacBeth (1973) regressions of this month's return on stock characteristics available at the end of last month. CoMove is defined as the frequency of equally signed monthly stock and market (S&P 500) returns during the last 36 months. For definitions of other variables, see Internet Appendix C. The sample covers all $\geq$ \$1 U.S. common stocks traded on the NYSE and AMEX from 1963 to 2015. t-statistics are based on Newey and West (1987) standard errors with one lag and are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Internet Appendix for "The Perception of Dependence, Investment Decisions, and Stock Prices"

Abstract

The Internet Appendix consists of five sections. Internet Appendix A contains additional tables, which are discussed in Internet Appendix B. Internet Appendix C defines the main variables used in the study and gives detailed data sources. In Internet Appendix D, we provide an overview of the experimental setup. Internet Appendix E contains the instructions and questions from the experiments.

A Additional Tables

Table A1: Experiment 1 – Other Portfolio Outcomes

Panel A shows participants' beliefs about the return characteristics of their selected portfolios. Additionally, for each statistic, the estimation error relative to the value based on the true portfolio return distribution is given. Panel B shows participants' subjective assessment of their portfolio selection. In addition to the respective variable's average value, the difference between the treatment two and one (2m1), three and two (3m2), and three and one (3m1) averages is reported. Treatments 1, 2, and 3 exhibit correlations between stock returns of -0.6, 0.2, and 0.6, respectively. Standard errors are in brackets. 1/2/3 stars denote significance at the 10/5/1%-level.

	Treatment					
	1	2	3	2m1	3m2	3m1
Panel A: Portfolio Beliefs						
E(Value)	11549.50***	11743.35***	12050.89***	193.86	307.54	501.39
	(271.61)	(393.11)	(240.26)	(436.68)	(436.68)	(436.68)
Error	1090.62***	1282.29***	1582.75***	191.67	300.47	492.13
	(271.63)	(393.23)	(240.46)	(436.84)	(436.84)	(436.84)
P(return$<$ 0%)	31.14***	28.84***	28.24***	-2.30	-0.60	-2.90
	(1.39)	(1.43)	(1.31)	(1.95)	(1.95)	(1.95)
Error	9.11***	-8.12***	-16.35***	-17.23***	-8.23***	-25.46***
	(2.05)	(1.62)	(1.39)	(2.41)	(2.41)	(2.41)
P(return< -20%)	14.84***	11.91***	12.11***	-2.94*	0.20	-2.73*
	(1.34)	(1.00)	(1.00)	(1.59)	(1.59)	(1.59)
Error	13.59***	8.78***	8.02***	-4.81***	-0.76	-5.57***
	(1.35)	(1.00)	(1.00)	(1.60)	(1.60)	(1.60)
P(return$>$ 20%)	28.69***	30.96***	32.47***	2.27	1.51	3.78
	(1.88)	(2.09)	(2.19)	(2.91)	(2.91)	(2.91)
Error	26.84***	27.52***	28.09***	0.68	0.57	1.24
	(1.86)	(2.08)	(2.19)	(2.90)	(2.90)	(2.90)
Panel B: Subjective Assessment of Portfolio Selection						
Portfolio Risk	4.30***	4.05***	3.98***	-0.25	-0.07	-0.32*
(1-7)	(0.12)	(0.13)	(0.13)	(0.18)	(0.18)	(0.18)
Confidence	4.22***	4.45***	4.61***	0.23	0.17	0.39**
(1-7)	(0.13)	(0.13)	(0.12)	(0.18)	(0.18)	(0.18)
Informedness	3.50***	3.43***	3.51***	-0.06	0.08	0.02
(1-7)	(0.13)	(0.13)	(0.14)	(0.19)	(0.19)	(0.19)

Table A2: Experiment 2 – Other Portfolio Outcomes

Panel A shows participants' beliefs about the return characteristics of their selected portfolios. Additionally, for each statistic, the estimation error relative to the value based on the true portfolio return distribution is given. Panel B shows participants' subjective assessment of their portfolio selection. In addition to the respective variable's average value, the difference between the treatment two and one (2m1) averages is reported. Treatment 1 exhibits negative dependence in extreme returns and positive dependence in moderate returns. Treatment 2 exhibits positive dependence in extreme returns and negative dependence in moderate returns. Standard errors are in brackets. 1/2/3 stars denote significance at the 10/5/1%-level.

		Treatment	
	1	2	2m1
Panel A: Portfolio Beliefs			
E(Value)	11398.16***	11481.13***	82.97
	(356.83)	(396.52)	(533.44)
Error	934.20**	1020.95**	86.75
	(357.29)	(396.63)	(533.83)
P(return< 0%)	29.26***	30.79***	1.53
	(1.63)	(1.56)	(2.26)
Error	-19.63***	14.78***	34.40***
	(1.62)	(2.48)	(2.96)
P(return< −20%)	13.44***	13.73***	0.30
	(1.36)	(1.15)	(1.78)
Error	12.90***	8.73***	-4.17**
	(1.39)	(1.15)	(1.81)
P(return> 20%)	31.06***	27.90***	-3.15
	(2.35)	(2.27)	(3.27)
Error	29.68***	22.90***	-6.78**
	(2.39)	(2.27)	(3.30)
Panel B: Subjective Assessment of Portfolio Selection			
Portfolio Risk	4.28***	4.29***	0.01
(1-7)	(0.15)	(0.16)	(0.22)
Confidence	4.17***	4.01***	-0.16
(1-7)	(0.15)	(0.16)	(0.22)
Informedness	3.24***	3.03***	-0.21
(1-7)	(0.15)	(0.14)	(0.21)

Table A3: Experiment 3 – Other Portfolio Outcomes

Panel A shows participants' beliefs about the return characteristics of their selected portfolios. Additionally, for each statistic, the estimation error relative to the value based on the true portfolio return distribution is given. Panel B shows participants' subjective assessment of their portfolio selection. In addition to the respective variable's average value, the difference between the treatment two and one (2m1) averages is reported. Treatment 1 exhibits negative correlation, negative dependence in extreme returns and positive dependence in moderate returns. Treatment 2 exhibits positive correlation, positive dependence in extreme returns and negative dependence in moderate returns. Standard errors are in brackets. 1/2/3 stars denote significance at the 10/5/1%-level.

		Treatment	
	1	2	2m1
Panel A: Portfolio Beliefs			
E(Value)	11116.78***	11132.28***	15.50
	(248.09)	(248.66)	(351.25)
Error	648.51**	673.30***	24.79
	(247.82)	(248.53)	(350.97)
P(return< 0%)	27.50***	28.43***	0.93
	(1.56)	(1.46)	(2.14)
Error	-21.57***	6.61***	28.18***
	(1.59)	(2.35)	(2.84)
P(return< −20%)	14.11***	14.20***	0.08
	(1.41)	(1.30)	(1.92)
Error	13.18***	8.78***	-4.40**
	(1.46)	(1.37)	(2.00)
P(return> 20%)	27.99***	28.11***	0.12
	(2.24)	(2.09)	(3.06)
Error	26.12***	15.12***	-11.00**
	(2.20)	(2.73)	(3.51)
Panel B: Subjective Assessment of Portfolio Selection			
Portfolio Risk	4.21***	4.13***	-0.07
(1-7)	(0.14)	(0.13)	(0.17)
Confidence	4.09***	4.13***	0.04
(1-7)	(0.15)	(0.14)	(0.12)
Informedness	3.34***	3.39***	0.06
(1-7)	(0.13)	(0.14)	(0.13)

Table A4: Experiment 4 – Other Portfolio Outcomes

Panel A shows participants' beliefs about the return characteristics of their selected portfolios. Additionally, for each statistic, the estimation error relative to the value based on the true portfolio return distribution is given. Panel B shows participants' subjective assessment of their portfolio selection. In addition to the respective variable's average value, the difference between the treatment two and one (2m1) averages is reported. Treatment 1 exhibits negative correlation, negative dependence in extreme returns and positive dependence in moderate returns. Treatment 2 exhibits positive correlation, positive dependence in extreme returns and negative dependence in moderate returns. Standard errors are in brackets. 1/2/3 stars denote significance at the 10/5/1%-level.

	Return-Treatment			Price-Treatment		
	1	2	2m1	1	2	2m1
Panel A: Portfolio Beliefs						
E(Value)	11485.69***	10898.21***	-587.48**	11343.18***	11911.36***	568.17
	(182.20)	(233.82)	(296.43)	(362.25)	(334.36)	(492.98)
Error	1016.90***	438.67*	-578.23*	880.15**	1447.66***	567.51
	(181.98)	(233.61)	(296.1)	(362.40)	(333.99)	(492.82)
P(return< 0%)	27.30***	29.38***	2.07	27.50***	28.43***	0.93
	(1.66)	(1.79)	(2.44)	(1.56)	(1.46)	(2.14)
Error	-21.77***	2.47	24.25***	-21.57***	6.61***	28.18***
	(1.72)	(3.51)	(3.91)	(1.59)	(2.35)	(2.84)
P(return< −20%)	11.85***	12.94***	1.08	11.70***	13.30***	1.61
	(1.40)	(1.48)	(2.04)	(1.07)	(1.38)	(1.75)
Error	10.65***	7.93***	-2.71	10.84***	8.30***	-2.54
	(1.08)	(1.38)	(2.08)	(1.46)	(1.37)	(1.75)
P(return> 20%)	17.87***	19.45***	1.58	30.57***	30.99***	0.42
	(1.96)	(2.13)	(2.89)	(2.59)	(2.92)	(3.90)
Error	15.77***	3.56	-12.21***	29.05***	10.59***	-18.46***
	(1.95)	(3.53)	(4.03)	(2.64)	(3.68)	(4.53)
Panel B: Subjective Assessment of Portfolio Selection						
Portfolio Risk	4.27***	3.94***	-0.34	4.09***	3.96***	-0.13
(1-7)	(0.18)	(0.20)	(0.27)	(0.15)	(0.19)	(0.24)
Confidence	4.47***	4.50***	0.03	4.05***	4.24***	0.18
(1-7)	(0.18)	(0.19)	(0.26)	(0.18)	(0.18)	(0.25)
Informedness	3.79***	3.63***	-0.16	2.86***	3.07***	0.21
(1-7)	(0.18)	(0.17)	(0.25)	(0.16)	(0.17)	(0.23)

Table A5: Viewing Time of Extreme Events

ln(Viewing Time) is the log of viewing time in seconds for each price path. The independent variable is the number of extreme events for each path. FEs are fixed effects, the coefficients of which are not reported. Standard-errors are reported in brackets. 1/2/3 stars denote significance at the 10/5/1%-level.

	Experiment				
	1	2	3	4 (Returns)	4 (Prices)
	ln(Viewing Time)				
	(1)	(2)	(3)	(4)	(5)
Number of Extreme Events	0.0578***	0.1215***	0.0909***	0.1553***	0.0995***
	(0.0114)	(0.0172)	(0.0319)	(0.0208)	(0.0179)
Path FEs	YES	YES	YES	YES	YES
Round FEs	YES	YES	YES	YES	YES
Treatment FEs	YES	YES	YES	YES	YES
Subject FEs	YES	YES	YES	YES	YES
R^2	0.63	0.68	0.67	0.67	0.70
No. obs.	3810	1900	2140	1240	1520

Table A6: Summary Statistics – Asset Pricing Tests

	Panel A: Univarate Distributions					
Variable	Mean	Median	Std. Dev.	p10	p90	N
CoMove	0.6553	0.6667	0.1032	0.5278	0.7778	1,595,760
Return_{t}	0.0080	0.0000	0.1307	-0.1221	0.1393	1,595,760
ln(size)	18.6334	18.4431	2.3328	15.7591	21.7864	1,595,760
ln(B/M)	-0.3274	-0.2985	0.9438	-1.4504	0.7396	1,414,257
$\text{Return}_{\text{t-12,t-2}}$	0.1503	0.0831	0.5434	-0.3459	0.6501	1,595,638
β	0.8899	0.8362	0.5249	0.2326	1.6868	1,595,760
β^-	0.9703	0.9135	0.5985	0.2327	1.8454	1,595,760
β^+	0.8073	0.7526	0.6407	0.0183	1.7521	1,595,760
LTD	0.1038	0.0817	0.0971	0.0000	0.2676	1,507,768
UTD	0.0761	0.0601	0.0740	0.0000	0.1986	1,507,768
Idio. Vola.	0.0206	0.0165	0.0138	0.0080	0.0383	1,594,599
Min	0.0462	0.0368	0.0323	0.0165	0.0878	1,594,599
Max	0.0553	0.0421	0.0422	0.0179	0.1108	1,594,599
Idio. Skew.	0.5113	0.4224	0.7574	-0.3124	1.4454	1,595,760

	Panel B: Correlations													
	CoMove	Return_{t}	ln(size)	ln(B/M)	$\text{Return}_{\text{t-12,t-2}}$	β	β^{-}	β^{+}	LTD	UTD	Idio. Vola.	Min	Max	Idio. Skew.
CoMove	1.0000													
Return_{t}	0.0170	1.0000												
ln(size)	0.0938	-0.0234	1.0000											
ln(B/M)	0.0013	0.0404	-0.4664	1.0000										
$\text{Return}_{\text{t-12,t-2}}$	0.0372	0.0170	0.0644	-0.2592	1.0000									
β	0.3212	0.0002	0.0566	-0.0774	0.0736	1.0000								
β^{-}	0.2385	0.0006	-0.0045	-0.0865	0.1050	0.8316	1.0000							
β^{+}	0.3061	0.0015	0.0992	-0.0441	0.0257	0.8467	0.4389	1.0000						
LTD	0.2051	-0.0126	0.1557	-0.1103	0.0769	0.3363	0.4188	0.1491	1.0000					
UTD	0.1504	-0.0063	0.0993	0.0303	-0.0993	0.1974	-0.0412	0.3599	0.2201	1.0000				
Idio. Vola.	-0.1563	0.0056	-0.3916	0.2055	-0.0897	0.1080	0.1360	0.0496	-0.1046	-0.0195	1.0000			
Min	-0.0837	0.0059	-0.3118	0.204	-0.0651	0.1688	0.1780	0.1106	-0.0254	0.0304	0.8009	1.0000		
Max	-0.0861	0.0007	-0.3131	0.1573	-0.0702	0.1637	0.1695	0.1125	-0.0467	0.0098	0.8769	0.6255	1.0000	
Idio. Skew.	-0.0783	0.0010	-0.2024	0.0185	0.2288	-0.0002	0.0364	-0.0347	0.0249	-0.1285	0.1618	0.0399	0.2105	1.0000

In this table, we report summary statistics for our main variables. CoMove is defined as the frequency of equally signed monthly stock and market (S&P 500) returns during the last 36 months. For variable definitions, see Internet Appendix C. The statistics are based on pooled observations of all $\geq$ \$1 U.S. common stocks traded on the NYSE and AMEX between 1963 and 2015.

Table A7: Fama/MacBeth Regressions: Robustness

	Panel A: Other Benchmarks, Fixed Effects, Skipped Month					
	(1)	(2)	(3)	(4)	(5)	(6)
CoMove	0.0119***	0.0117***	0.0102***	0.0100***	0.0091***	0.0132***
	(4.58)	(4.84)	(4.02)	(3.58)	(4.68)	(5.64)
β	-0.0014	-0.0016	-0.0019	-0.0016	-0.0022	-0.0016
	(-0.86)	(-0.98)	(-1.25)	(-1.01)	(-1.52)	(-1.04)
ln(Size)	-0.0006	-0.0006	-0.0005	-0.0005	-0.0021***	-0.0006
	(-1.31)	(-1.47)	(-1.30)	(-1.29)	(-3.60)	(-1.46)
ln(B/M)	0.0013**	0.0018***	0.0018***	0.0012*	0.0033***	0.0028***
	(2.30)	(3.91)	(3.50)	(1.81)	(7.26)	(5.60)
$\text{Ret}_{\text{t-12,t-2}}$		0.0084***	0.0084***		0.0086***	0.0097***
		(5.57)	(5.83)		(7.15)	(7.03)
$\text{Ret}_{\text{t-1,t-1}}$		-0.0423***	-0.0430***			
		(-11.07)	(-10.84)			
$\text{Ret}_{\text{t-36,t-13}}$		-0.0006	-0.0007			
		(-1.23)	(-1.39)			
Op.Profitability			0.0017**	0.0014**		
			(2.41)	(2.04)		
Asset Growth			-0.0042***	-0.0052***		
			(-6.20)	(-7.29)		
Average R^2	5.06%	6.92%	7.21%	5.30%	13.18%	5.81%
Average N	1718	1678	1267	1269	1712	1716
T	636	636	636	636	636	636
FF48-FEs	No	No	No	No	Yes	No
Size-Decile-FEs	No	No	No	No	Yes	No
Exchange-FEs	No	No	No	No	Yes	No
1 month skipped	No	No	No	No	No	Yes

Panel B: Varying the CoMov-Measure and the Sample								
	(1) weekly freq.	(2) daily freq.	(3) value-w. mkt	(4) with NAS-DAQ	(5) without small	(6) with Prc$\geq$ 5	(7) Pre-1988	(8) Post-1989
CoMove	0.0160***	0.0351***	0.0104***	0.0134***	0.0116***	0.0118***	0.0107***	0.0129***
	(5.17)	(5.16)	(3.89)	(5.38)	(4.77)	(5.44)	(3.20)	(3.55)
β	-0.0021	-0.0033*	-0.0016	-0.0012	-0.0017	-0.0018	-0.0019	-0.0013
	(-1.29)	(-1.83)	(-1.03)	(-0.77)	(-0.99)	(-1.11)	(-1.06)	(-0.52)
ln(Size)	-0.0007*	-0.0010***	-0.0005	-0.0008*	-0.0006*	-0.0005	-0.0011*	-0.0000
	(-1.74)	(-2.66)	(-1.35)	(-1.81)	(-1.69)	(-1.44)	(-1.79)	(-0.01)
ln(B/M)	0.0028***	0.0027***	0.0029***	0.0036***	0.0022***	0.0026***	0.0040***	0.0017***
	(5.53)	(5.35)	(5.67)	(6.74)	(4.16)	(5.18)	(5.23)	(2.64)
$\text{Ret}_{\text{t-12,t-2}}$	0.0094***	0.0096***	0.0096***	0.0091***	0.0087***	0.0089***	0.0131***	0.0063***
	(6.85)	(6.99)	(7.00)	(8.23)	(5.65)	(6.67)	(7.61)	(2.99)
Average R^2	5.83%	5.90%	5.84%	4.88%	7.21%	6.28%	6.79%	4.88%
Average N	1719	1719	1718	3304	1255	1513	1807	1633
T	636	636	636	636	636	636	312	324

In this table, we report results from Fama and MacBeth (1973) regressions of this month's return on stock characteristics available at the end of last month. In Panel A and Specifications (4) to (8) of Panel B CoMove is defined as the frequency of equally signed monthly stock and market (S&P 500) returns during the last 36 months. In the first (second) Specification of Panel B CoMove is defined as the frequency of equally signed weekly (daily) stock and market (S&P 500) returns during the last 52 weeks (260 days). In the third Specification of Panel B we use CRSP's value-weighted market return instead of the S&P 500 return. For definitions of other variables, see Internet Appendix C. The sample covers all $\geq$ \$1 U.S. common stocks traded on the NYSE and AMEX from 1963 to 2015. t-statistics are based on Newey and West (1987) standard errors with one lag and are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

B Discussion of Additional Tables

B.1 Experimental Evidence

Tables A1 through A4 in Internet Appendix A report further outcome variables, which show that participants do not correctly answer questions about the riskiness of their portfolio returns. The finding that investors cannot aggregate stock level variances and dependencies to portfolio level returns is consistent with results from Merkle (2016) and Reinholtz, Fernbach, and de Langhe (2016). The consistency between perceived dependence and diversification decisions in our four experiments shows however, that it is not necessary for participants to correctly aggregate to portfolio returns for dependence to have an impact on portfolio selection. Understanding what happens to asset B when asset A increases in value, i.e. understanding dependence, is enough for an effect on the investment decision.

We collect participants' beliefs about portfolio characteristics (panel A) and their subjective assessment of the portfolio selection decision (panel B). Their beliefs about aggregate portfolio characteristics do not react significantly to the treatments, even though actual portfolio characteristics change a lot. As an illustration, the probability of a negative portfolio return for the average participant in experiment 1 (Table A1) increases by around 22% (from 22% to 44%) as correlation increases from treatment 1 to treatment 3. However, participants' estimate for the probability of negative returns does not change significantly, staying between 28% and 32%. Subjective assessments of the portfolio selection decision do not change strongly over the treatments either. Hence, even though our main analysis shows that participants' beliefs and choices react to changes in dependence over treatments, these results indicate that participants cannot properly aggregate their beliefs about dependence to make reasonable statements about the riskiness of portfolio returns.

Table A4 reports further outcome variables separately for participants who see return series and those who see price paths. As for experiments 1, 2 and 3, participants' beliefs about aggregate portfolio characteristics usually do not react significantly to the treatments, even though actual portfolio characteristics change a lot. Subjective assessments of the portfolio selection decision do not change significantly over the treatments either. However, subjects state significantly higher levels of confidence and informedness in the return series group (statistical significance of 10% for confidence and 1% for informedness). These assessments are consistent with participants' stronger treatment effects in the return group.

Table A5 reports the reaction of log-viewing times to the number of extreme events in a price path. One might argue that a reason for missing influence of extreme returns on beliefs and the investment decision is that extreme states–although in line with historical extreme observations (see Section 2.5)–are not salient enough. We can provide evidence against this argument. For all four experiments, paths with more extreme events are viewed significantly longer than paths with less extreme events. The mean differences in viewing times for each additional extreme event per 10-year path are 6% (experiment 1), 12% (experiment 2), 9% (experiment 3), 16% (experiment 4 with returns), and 10% (experiment 4 with price paths).

B.2 Stock Market Evidence

We report summary statistics for our asset pricing tests in Table A6 of Internet Appendix A. The first line of Panel A shows that the average (median) frequency of co-movement between stock and S&P 500 returns is 66% (67%). The 10^{th} (90^{th}) percentile of the CoMove distribution is at 53% (78%). In panel B we report correlations amongst our main variables. CoMove is positively related to β, which motivates controlling for β in asset pricing tests. It is also positively related to downside and upside risk (β^- and β^+, as well as LTD and UTD). Since downside risk is actually positively priced—in contrast to β—the omitted variable bias when downside risk is not controlled for is potentially severe. Measures of idiosyncratic risk are all negatively related to CoMove (e.g. idiosyncratic volatility at -0.16). Idiosyncratic risk is negatively priced, so that omitted variable bias may be a problem here as well. In the main text (Table 14), we show that none of these related measures of systematic and idiosyncratic risk explain the positive premium for CoMove.

In Panel A of Table A7 of Internet Appendix A we report additional Fama and MacBeth (1973) regressions. We include only the three Fama and French (1993) predictors, market risk, size and value in Specification (1). In Specification (2) we add short-, medium- and long-term past returns. And in Specifications (3) and (4) we add the additional predictors asset growth and profitability from Fama and French (2015). None of these additional control variables explain the positive premium for CoMove. It remains highly statistically significant at values beyond 3, and its economic significance remains stable at a high level. In Specification (5) we control for Fama/French-48 industry, exchange and NYSE-size-decile fixed effects. The CoMove premium remains significant. It is not driven by entire industries, small vs. large firm returns, or NYSE vs. AMEX returns. In Specification (6) we skip one month between the measurement period for CoMove and the prediction period for returns. CoMove remains significantly priced. It actually becomes larger, which shows that it is not driven by the returns of last month.

In Panel B of Table A7 of Internet Appendix A we vary the CoMove measure, the data requirements, and we split into the first and second half of our sample. All specifications in Panel B use the control variables market risk, size, book/market ratio and last year's return (Carhart (1997)). Using the last 52 weekly (260 daily) returns, or the CRSP value-weighted instead of the S&P 500 market return to measure CoMove also leads to a significant CoMove premium (Specifications (1) to (3)). Including NASDAQ stocks, excluding small firms below the 1^{st} NYSE-decile or stocks with end-of-last-month prices below \$5 does not change results either (Specifications (3) to (6)). As in the main analysis the 1989-2015 premium for CoMove is higher than the 1963-1988 premium. However, both are statistically and economically highly significant.

C Overview of Variables

The following table briefly defines the main variables collected in our experiments.

Panel A: Outcome Variables

Variable Name	Description
Viewing Time	The number of seconds a participant looks at each of the 10×10-year price paths.
Investment in Stock 2	'You have an endowment of 10'000 €. Your task is to invest this money in two stocks. How much do you invest into stock 2? (Note: The rest is invested in stock 1.)' (Any numerical answer between 0 and 10'000 could be typed in.)
Overall Dependence	'Stocks 1 and 2 move ...' (Three radiobuttons from 'in opposite directions' to 'together'.)
Downside Frequency of Comovement	'Given that stock 1's price decreases, I expect stock 2's price to increase in ... out of 100 cases.' (Any numerical answer from 0 to 100 was allowed.)
Upside Frequency of Comovement	'Given that stock 1's price increases, I expect stock 2's price to increase in ... out of 100 cases.' (Any numerical answer from 0 to 100 was allowed.)
Downside Dependence in Extreme Returns	'Given that stock 1's price decreases strongly (by more than 20%), I expect stock 2 to...' (Three radiobuttons from 'decrease' to 'increase'.)
Upside Dependence in Extreme Returns	'Given that stock 1's price increases strongly (by more than 20%), I expect stock 2 to...' (Three radiobuttons from 'decrease' to 'increase'.)
Downside Dependence in Moderate Returns	'Given that stock 1's price decreases moderately (by less than 20%), I expect stock 2 to...' (Three radiobuttons from 'decrease' to 'increase'.)
Upside Dependence in Moderate Returns	'Given that stock 1's price increases moderately (by less than 20%), I expect stock 2 to...' (Three radiobuttons from 'decrease' to 'increase'.)
Porfolio Value	'Given your investment decision, what do you expect your portfolio value to be in one year?' (Any numerical answer ≥ 0 was allowed.)
Loss Frequency	'In how many out of 100 cases do you expect to lose money (a final portfolio value of less than 10'000 € in one year)?' (Any numerical answer between 0 and 100 was allowed.)
Large Loss Frequency	'In how many out of 100 cases do you expect your final portfolio value to be less than 8'000 € in one year?' (Any numerical answer between 0 and 100 was allowed.)
Large Gain Frequency	'In how many out of 100 cases do you expect your final portfolio value to be more than 12'000 € in one year?' (Any numerical answer between 0 and 100 was allowed.)
Portfolio Risk	'How risky do you perceive your portfolio to be?' (Seven radiobuttons from 'risk-free' to 'very risky'.)
Confidence	'How confident are you about your investment decision?' (Seven radiobuttons from 'not confident at all' to 'very confident'.)
Informedness	'How informed do you feel when making this investment decision?' (Seven radiobuttons from 'not at all informed' to 'completely informed'.)

Panel B: Control Variables

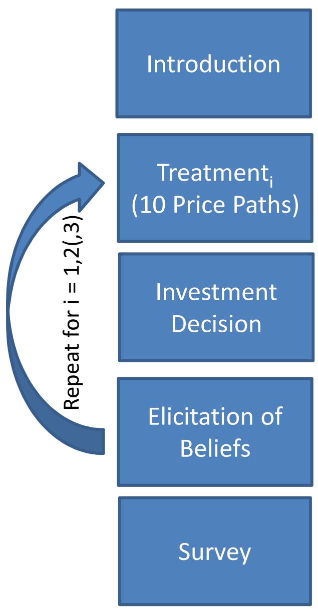
Variable Name	Description
Age	Age of the participant.
Gender	Gender of the participant.
Stock-Ownership	'Do you own stocks or an equity mutual fund?' (Answer: Yes or no.)
Financial Market Interest	'Are you generally interested in stock or financial markets?' (Answer: Yes or no.)
Risk Attitude	Self-reported: 'Please estimate your willingness to take financial risk.' (Five radiobuttons from 'not willing to accept any risk' to 'willing to accept substantial risk to potentially earn a greater return'.)
Statistics Course	'Have you attended a university statistics course?' (Answer: Yes or no.)
Statistics Knowledge	'How would you describe your knowledge about statistics?' (Four radiobuttons from 'good' to 'bad'.)
Financial Literacy	Financial Literacy Score between 0 and 12: The number of correct answers to twelve financial literacy questions from Fernandes, Lynch, and Netemeyer (2014). Item (8) from the original test was left out since the experiments were conducted in Germany (it is a question related to 401(k) plans and therefore specific to the US setting).
Numeracy	Numeracy Score between 0 and 4: The number of correct answers to the traditional format version of the Berlin Numeracy Test from Cokely, Galesic, Schulz, and Ghazal (2012).

Panel C: Financial Market Variables

Variable Name	Description
CoMove	Frequency of jointly positive or jointly negative return pairs between stock return and S&P 500 market return. Base case: Last 36 monthly returns. Robustness: last 52 (260) weekly (daily) returns.
β	Factor loading on the market factor from a CAPM one-factor regression estimated based on a 1-year rolling window of daily data: $\beta = \frac{\text{COV}(r_i, r_m)}{\text{VAR}(r_m)}$.
β^-	Downside beta estimated based on a 1-year rolling window of daily data, as defined in Ang, Chen, and Xing (2006): $\beta^- = \frac{\text{COV}(r_i, r_m \mid r_m < \mu_m)}{\text{VAR}(r_m \mid r_m < \mu_m)}$, where μ_m is the mean market return.
β^+	Upside beta. As β^-, but with inverted signs within the conditional (co)variance.
LTD	Lower tail dependence between stock returns and (value-weighted) market returns, from Chabi-Yo, Ruenzi, and Weigert (2015).
UTD	Upper tail dependence between stock returns and (value-weighted) market returns, from Chabi-Yo, Ruenzi, and Weigert (2015).
ln(size)	The log of a firm's equity market capitalization.
ln(B/M)	The log of a firm's book/market ratio, with ceq from CS as book-equity.
$\text{Ret}_{\text{t-12,t-2}}$	Last year's return, excluding the most recent month.
$\text{Ret}_{\text{t-1,t-1}}$	Last month's return.
$\text{Ret}_{\text{t-36,t-13}}$	The return of the two years prior to last year.

Panel C (continued): Financial Market Variables	
Variable Name	Description
Idio. Vola.	The standard-deviation of residuals from the Fama and French (1992)-model, estimated with last month's daily returns (≥ 10 observations required).
Max	A stock's maximum daily return last month, as in Bali, Cakici, and Whitelaw (2011).
Min	A stock's minimum daily return last month, multiplied by -1.
Idio. Skew.	The skewness of residuals from the Fama and French (1992)-model, estimated with last month's daily returns (≥ 10 observations required).
Amihud	Amihud (2002)'s illiquidity ratio, based on last year's daily returns and dollar-volumes.
ln(turn.)	The log of a firm's monthly turnover.
Δ ln(turn.)	The log-change of a firm's monthly turnover.
Operating Profitability	The firm's operating profitability, as in Fama and French (2015).
Asset Growth	Investments variable from Fama and French (2015).
Rm-Rf	Value-weighted market return over the one-month Treasury bill rate according to Kenneth French's data library.
SMB	Small minus big factor return according to Kenneth French's data library.
HML	High minus low factor return according to Kenneth French's data library.
MOM	Momentum factor return according to Kenneth French's data library.
MOM	Momentum factor return according to Kenneth French's data library.
ST	Short-term reversal factor return according to Kenneth French's data library.
LT	Long-term reversal factor return according to Kenneth French's data library.
FF-5F	Fama and French (2015) factor returns (2x3) according to Kenneth French's data library.
BAB	Betting-against-beta factor returns according to Frazzini and Pedersen (2014).
Kelly	Kelly and Jiang (2014) factor returns.
PS	Pástor and Stambaugh (2003) liquidity factor returns.
Sadka	Sadka (2006) liquidity factor returns.
UMO	Hirshleifer and Jiang (2010) (undervalued-minus-overvalued) factor returns.

D Overview of Experimental Setup



E Instructions and Questions

All instructions and questions, translated from German into English.

Introduction:

Screen 1 (Welcome Screen):

Dear participant,

the aim of this experiment is to better understand decision making of investors. The experiment consists of two sections. In section 1, an experiment is conducted, in the course of which you have to make 2 investment decisions. Section 2 is a survey.

For your participation in this experiment, you will receive a performance-based compensation, which depends on your 2 investment decisions in section 1 of the experiment. After the experiment, we will randomly select whether you will receive the compensation based on your first or second investment decision. You will receive your compensation after completing the survey.

The experiment will take (including time for reading of instructions, the survey, and the payout of your compensation) around 1 hour. We politely ask you to not communicate with other participants during the experiment. As soon as you leave this screen, section 1 of the experiment begins.

If you have any questions, please put your hand up.

Screen 2 (Instructions):

On the following screens, you will see simulated price paths of two stocks. Subsequently, you are supposed to split your fictive wealth of 10'000 € between the two stocks. The average return per year of stocks 1 and 2 is known:

Average return stock 1: 5% per year Average return stock 1: 4% per year

You will receive a compensation that is based on your investment decision. We calculate this compensation based on a simulation of a one-year stock return for each of the two stocks, according to the following formula:

`[Investment_Stock1*(1*Return_Stock1)+Investment_Stock2*(1*Return_Stock2)]/1'000`

Example: Assume you have split your wealth evenly between stocks 1 and 2. The simulation results in a yearly return of -10% for stock 1 and +20% for stock 2. Your fictive wealth is then 5'000 € * (1-10%) + 5'000 € * (1+20%) = 5'000 € * 0.9 + 5'000 € * 1.2 = 10'500 €. Your performance-based compensation is therefore 10'500 € / 1'000 = 10,50 €

Comprehension questions: Assume you have invested 2'000 € of your wealth into stock 2. The simulation results in a return of +25% for stock 1 and -25% for stock 2. What is your fictive wealth at the end of this investment round?

As soon as you click 'Continue', the experiment will begin.

Treatment$_{\mathbf{i}}$ (10 Price Paths):

Screen 3 (Introduction to Treatment i):

Round i of the experiment starts now.

After this screen, you will see simulated price paths of two stocks. Based on these price paths you can get an idea of possible joint realizations for these stocks. Subsequently, you are supposed to split your fictive wealth of 10'000 € between the two stocks. Your compensation at the end of the experiment depends on this investment decision and newly simulated returns of both stocks.

Screens 4-13 (Treatment i):

[Participants view 10 × 10-year price paths for the current treatment. Participants determine themselves how long to view each path and click 'continue to next price path' (paths 1-9) or 'continue to investment decision' (path 10) to continue. After moving on from each price path, they cannot go back. The heading of each screen shows the number of price paths already viewed, e.g. 'price path 5 out of 10'.]

Investment Decision:

Screen 14:

Your have 10'000 € at your disposal. Your task is to split this wealth between the two stocks. How much do you want to invest in stock 2? (Note: The remainder will automatically be invested in stock 1.)

Investment in stock 2 (in €):

Elicitation of Beliefs:

Screen 15 (Dependence):

- 'Stocks 1 and 2 move ...' (Three radiobuttons from 'in opposite directions' to 'together'.)
- 'Given that stock 1's price decreases strongly (by more than 20%), I expect stock 2 to...' (Three radiobuttons from 'decrease' to 'increase'.)
- 'Given that stock 1's price increases strongly (by more than 20%), I expect stock 2 to...' (Three radiobuttons from 'decrease' to 'increase'.)
- 'Given that stock 1's price decreases moderately (by less than 20%), I expect stock 2 to...' (Three radiobuttons from 'decrease' to 'increase'.)
- 'Given that stock 1's price increases moderately (by less than 20%), I expect stock 2 to...' (Three radiobuttons from 'decrease' to 'increase'.)
- 'Given that stock 1's price decreases, I expect stock 2's price to increase in ... out of 100 cases.' (Any numerical answer from 0 to 100 was allowed.)

- 'Given that stock 1's price increases, I expect stock 2's price to increase in ... out of 100 cases.' (Any numerical answer from 0 to 100 was allowed.)

Screen 16 (Portfolio Characteristics):

- 'Given your investment decision, what do you expect your portfolio value to be in one year?' (Any numerical answer ≥ 0 was allowed.)
- 'In how many out of 100 cases do you expect to lose money (a final portfolio value of less than 10'000 € in one year)?' (Any numerical answer between 0 and 100 was allowed.)
- 'In how many out of 100 cases do you expect your final portfolio value to be more than 12'000 € in one year?' (Any numerical answer between 0 and 100 was allowed.)
- 'In how many out of 100 cases do you expect your final portfolio value to be less than 8'000 € in one year?' (Any numerical answer between 0 and 100 was allowed.)
- 'How risky do you perceive your portfolio to be?' (Seven radiobuttons from 'risk-free' to 'very risky'.)
- 'How confident are you about your investment decision?' (Seven radiobuttons from 'not confident at all' to 'very confident'.)
- 'How informed do you feel when making this investment decision?' (Seven radiobuttons from 'not at all informed' to 'completely informed'.)

Survey:

Screen 17 (Basic Characteristics):

- Self-reported: 'Please estimate your willingness to take financial risk.' (Five radiobuttons from 'not willing to accept any risk' to 'willing to accept substantial risk to potentially earn a greater return'.)
- 'Do you own stocks or an equity mutual fund?' (Answer: 'yes' or 'no'.)

- 'Are you generally intersted in stock or financial markets?' (Answer: 'yes' or 'no'.)
- 'Do you own stocks or an equity mutual fund?' (Answer: 'yes' or 'no'.)
- 'Have you attended a university statistics course?' (Answer: 'yes' or 'no'.)
- 'How would you describe your knowledge about statistics?' (Four radiobuttons from 'good' to 'bad'.)
- 'What's your age?' (Answer: Any numerical answer between 16 and 80 was allowed.)
- 'Are you male or female?' (Answer: 'male' or 'female'.)

Screen 18 (Financial Literacy I):

- Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, would you be able to buy:
  - More than today with the money in this account
  - Exactly the same as today with the money in this account
  - *Less than today with the money in this account*
  - Don't know
  - Refuse to answer

  (Item (1) from Fernandes, Lynch, and Netemeyer (2014).)
- Do you think that the following statement is true or false? 'Bonds are normally riskier than stocks.'
  - True
  - *False*
  - Don't know
  - Refuse to answer

  (Item (2) from Fernandes, Lynch, and Netemeyer (2014).)

- Considering a long time period (for example, 10 or 20 years), which asset described below normally gives the highest return?
    - Savings accounts
    - *Stocks*
    - Bonds
    - Don't know
    - Refuse to answer

  (Item (3) from Fernandes, Lynch, and Netemeyer (2014).)

- Normally, which asset described below displays the highest fluctuations over time?
    - Savings accounts
    - *Stocks*
    - Bonds
    - Don't know
    - Refuse to answer

  (Item (4) from Fernandes, Lynch, and Netemeyer (2014).)

Screen 19 (Financial Literacy II):

- When an investor spreads his money among different assets, does the risk of losing a lot of money:
    - Increase
    - *Decrease*
    - Stay the same
    - Don't know
    - Refuse to answer

(Item (5) from Fernandes, Lynch, and Netemeyer (2014).)

- Do you think that the following statement is true or false? 'If you were to invest 10'000 € in a stock mutual fund, it would be possible to have less than 10'000 € when you withdraw your money.'
  - *True*
  - False
  - Don't know
  - Refuse to answer

  (Item (6) from Fernandes, Lynch, and Netemeyer (2014).)

- Do you think that the following statement is true or false? 'A stock mutual fund combines the money of many investors to buy a variety of stocks.'
  - *True*
  - False
  - Don't know
  - Refuse to answer

  (Item (7) from Fernandes, Lynch, and Netemeyer (2014).)

- Do you think that the following statement is true or false? 'A 15-year mortgage typically requires higher monthly payments than a 30-year mortgage, but the total interest paid over the life of the loan will be less.'
  - *True*
  - False
  - Don't know
  - Refuse to answer

  (Item (9) from Fernandes, Lynch, and Netemeyer (2014).)

Screen 20 (Financial Literacy III):

- Suppose you have 100 € in a savings account and the interest rate is 20% per year and you never withdraw money or interest payments. After 5 years, how much would you have in this account in total?
  - *More than 200 €*
  - Exactly 200 €
  - Less than 200 €
  - Don't know
  - Refuse to answer

  (Item (10) from Fernandes, Lynch, and Netemeyer (2014).)

- Which of the following statements is correct?
  - Once one invests in a mutual fund, one cannot withdraw the money in the first year
  - *Mutual funds can invest in several assets, for example in both stocks and bonds*
  - Mutual funds pay a guaranteed rate of return which depends on their past performance
  - None of the above
  - Don't know
  - Refuse to answer

  (Item (11) from Fernandes, Lynch, and Netemeyer (2014).)

- Which of the following statements is correct? If somebody buys a bond of firm B:
  - He owns a part of firm B
  - *He has lent money to firm B*
  - He is liable for firm BÆs debts

- None of the above
- Don't know
- Refuse to answer

(Item (12) from Fernandes, Lynch, and Netemeyer (2014).)

- Suppose you owe 3'000 € on your credit card. You pay 30 € each month. At an annual percentage rate of 12% (or 1% per month), how many years would it take to eliminate your credit card debt if you made no additional new charges?
  - Less than 5 years
  - Between 5 and 10 years
  - Between 10 and 15 years
  - *Never*
  - Don't know
  - Refuse to answer

  (Item (13) from Fernandes, Lynch, and Netemeyer (2014).)

Note: This test is an adapted version of the financial literacy test in Fernandes, Lynch, and Netemeyer (2014). Item (8) from the original test was left out since the experiments were conducted in Germany (it is a question related to 401(k) plans and therefore specific to the US setting).

Screen 21 (Numeracy):

- 'Out of 1,000 people in a small town 500 are members of a choir. Out of these 500 members in a choir 100 are men. Out of the 500 inhabitants that are not in a choir 300 are men. What is the probability that a randomly drawn man is a member of the choir? Please indicate the probability in percent. This means that you should not use any commas or dots.' (Numerical answer between 0 and 100. Correct answer: 25)

- 'Imagine we are throwing a five-sided die 50 times. On average, out of these 50 throws how many times would this five-sided die show an odd number (1, 3 or 5)?' (Numerical answer between 0 and 50. Correct answer: 30)

- 'Imagine we are throwing a loaded die (6 sides). The probability that the die shows a 6 is twice as high as the probability of each of the other numbers. On average, out of these 70 throws how many times would the die show the number 6?' (Numerical answer between 0 and 70. Correct answer: 20)

- 'In a forest 20% of mushrooms are red, 50% brown and 30% white. A red mushroom is poisonous with a probability of 20%. A mushroom that is not red is poisonous with a probability of 5%. What is the probability that a poisonous mushroom in the forest is red?' (Numerical answer between 0 and 100. Correct answer: 50)

Note: This test is the traditional format version of the Berlin Numeracy Test from Cokely, Galesic, Schulz, and Ghazal (2012).