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Irrational Diversification; An Examination of Individual Portfolio Choice

Guido Baltussen and Gerrit T. Post*

Abstract

We study individual portfolio choice in a laboratory experiment and find strong evidence for heuristic behavior. The subjects tend to focus on the marginal distribution of an asset, while largely ignoring its diversification benefits. They follow a conditional 1/*n* diversification heuristic as they exclude the assets with an "unattractive" marginal distribution and divide the available funds equally between the remaining, "attractive" assets. This strategy is applied even if it leads to allocations that are dominated in terms of first-order stochastic dominance and is clearly irrational. In line with these findings, we find that framing and problem presentation have substantial influence on portfolio decisions.

* Baltussen, guidobaltussen@gmail.com, Erasmus School of Economics, Burgemeester Oudlaan 50, Rotterdam 3000 DR, The Netherlands and Stern School of Business, New York University, 44 West Fourth Street, New York, NY 10012-1126, USA; Post, Koç University Graduate School of Business, Istanbul, Turkey. Please mail any questions or enquiries to the first author. Financial support by Tinbergen Institute, Erasmus Research Institute of Management, Erasmus Center of Financial Research, Erasmus Trustfonds, and Robeco Asset Management is gratefully acknowledged. We thank an anonymous referee, Shlomo Benartzi, Werner De Bondt, Haim Levy, Kasper Meisner Nielsen, Jaap Spronk, Philippe Versijp, Pim van Vliet and seminar participants at the BDRM conference in San Diego, the FMA meeting in New York, the Erasmus School of Economics, University of Amsterdam, and Tinbergen Institute for very helpful comments and discussions. Any remaining errors are the authors' responsibility.

I. Introduction

Portfolio construction is an important economic task for individual investors and money managers. Modern portfolio theory, dating back to the seminal work of Markowitz (1952, 1959), says that an investor should optimize her portfolio's return-risk-exposure trade-off by carefully spreading out her scarce resources over various assets. Unfortunately, this task is generally quite demanding, as infinitely many possible combinations have to be considered. In addition, the investor has to consider not only the individual assets but also the statistical association between them. Indeed, psychological work by Tversky and Kahneman (1981), Simon (1955, 1979), Payne, Bettman and Johnson (1992), and many others suggests that the portfolio choice task may be too complex for decision makers to perform, and decision makers adopt various kinds of simplifying diversification heuristics in practice, as first shown by Simonson (1990) and Read and Loewenstein (1995).

The choices of participants in defined contribution pension plans are a case in point, as shown among others by Benartzi and Thaler (BT; 2001) and Huberman and Jiang (HJ; 2006). When the number of funds offered (n) is relatively small, plan participants seem to employ a naïve diversification strategy of investing an equal fraction ($1/n$) in all funds offered in the plan.[1] Thus, the number of funds chosen increases as the number of funds offered increases and the fraction invested in equity increases as the fraction of equity funds offered increases. This behavior seems suboptimal, because the framing of the investment problem does not alter the participant's optimal fund allocation. Furthermore, when the number of funds offered becomes larger, participants seem to apply the $1/n$ rule to a subset of the funds offered. For example, in the HJ study, the median number of funds chosen is three, compared with a median number of funds offered of 13.[2] HJ refer to this phenomenon as the "conditional $1/n$ diversification heuristic."

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[1] This bias towards an equal distribution over the presented alternatives is also documented for many other economic decisions (see Fox and Clemen (2005), Fox, Ratner and Lieb (2005), and Sonnemann, Camerer, Langer, and Fox (2008)).

[2] Similar results are found by Friend and Blume (1975), Goetzmann and Kumar (2005) and Polkovnichenko (2005) for individual stock portfolio holdings. They show that the median number of stocks held in a portfolio is two to three.

In this paper, we shed more light on the nature and optimality of the portfolio construction decision and the use of diversification heuristics. One compelling explanation for the conditional 1/*n* heuristic is that decision makers frame their investment decisions narrowly and assign too much weight to the marginal distribution of the outcomes of the individual choice alternatives.[3] They may exclude the alternatives that are unattractive (that is, they yield small potential gains and large potential losses) when held in isolation, without fully accounting for their possible diversification benefits. Decision makers may then apply the 1/*n* heuristic to the remaining alternatives, possibly because the remaining alternatives look very similar.

This explanation is reminiscent of the "Elimination-By-Aspects" (EBA) theory (Tversky (1972)), which says that decision makers compare alternatives on their most salient or desirable features, and eliminate alternatives that fall short on these aspects. Payne (1976) and Payne, Bettman and Johnson (1993) find that decision makers may use simple strategies such as the EBA to reduce the choice set before applying a more complex, trade-off strategy to the remaining alternatives. The explanation is also consistent with the findings of Kroll, Levy and Rapoport (1988), Kroll and Levy (1992), and Dorn and Huberman (2010) who show that decision makers are largely insensitive to statistical association between investment alternatives. In addition, the explanation aligns with the Behavioral Portfolio Theory (BPT) of Shefrin and Statman (2000). BPT says that an investor does not consider her investments as one integrated portfolio but rather as a collection of narrowly framed sub-portfolios, each based on a separate risk-return trade-off that ignores the statistical association between the various sub-portfolios.

The conditional 1/*n* heuristic can have substantial practical consequences. For example, for pension plans, this behavior may lead participants to focus on a subset of funds in the same, "attractive" asset class. In this respect, financial advisors stressing the benefits of diversification between asset classes and plans including mixed-funds

[3] Although we use the term narrow framing, other terms for this behavior are used in the literature as well. For example, Thaler (1985, 1999) speaks of mental accounting, and Read, Loewenstein and Rabin (1999) speak of narrow bracketing. The relevance of narrow framing for describing investment decisions is shown by Barberis, Huang and Thaler (2006), and the tendency to frame investment decisions narrowly seems especially pronounced for household investors (see Kumar and Lim (2008)).

could help improve pension investment. At the level of the aggregate capital market, Barberis and Huang (2001) show that a number of "anomalous" asset pricing patterns naturally emerge if investors care about fluctuations in individual stocks instead of fluctuations in their total portfolios.

Important challenges arise when analyzing real-life investment portfolios. The researcher needs to know (among other things) the investor's risk preferences, which assets she considers, and the expectations she has about these assets, most of which are generally hard to measure or control. To overcome this joint hypothesis problem, we use a controlled experiment among financially well-trained subjects. The experiment employs incentive-compatible payoffs (on average a subject earns roughly €50 ($75)) to ensure that subjects' decisions have substantial consequences. Moreover, the experiment avoids the situation where the subject adopts a heuristic because the choice alternatives are not sufficiently different or to diversify away estimation or ambiguity risk.

This is how our experiment works. Subjects are presented with five sets of assets and asked to form a portfolio from each set. To avoid specific assumptions about the nature of the subject's risk preferences, and at the same time gauge the optimality of choices, we analyze the optimality of the chosen portfolios using the criterion of first-order stochastic dominance (FSD). This criterion only requires that the decision maker prefers more over less. FSD is a minimal requirement for rational behavior in expected utility theory and many non-expected utility theories, such as cumulative prospect theory (Tversky and Kahneman (1992)) and disappointment aversion theory (Gul (1991)). In fact, FSD violations may be regarded as errors rather than genuine expression of preferences (see Tversky and Kahneman (1986), and Charness, Karni and Levin (2007)). Using the novel FSD portfolio efficiency tests of Kuosmanen (2004) (see also Kopa and Post (2009)), we can directly test if a given allocation is rational without knowing the precise risk preferences of the subject. To control for expectations and assets considered, and to minimize the cognitive complexity of the portfolio construction problem, we use a series of well-defined and simple tasks. In these tasks, subjects have to divide their money between a small number of assets, or "lotteries", with a small number of equally likely states with known outcomes. One of the lotteries is very unattractive when held in isolation, but very attractive for diversification purposes due to a negative statistical association with the other lotteries. Another lottery is more attractive in isolation, but very unattractive for diversification purposes. In fact, the inclusion of this lottery in one's portfolio will lead to substantial violations of FSD portfolio efficiency. These lotteries are included to test the hypothesis that decision makers overweight the marginal distribution and underweight the features of the joint distribution.

The use of the FSD portfolio efficiency criterion is an innovation in this literature. This criterion has several advantages for experimental research; it places no restrictions on risk attitudes (it even allows for risk seeking); it is invariant to subjective distortions of cumulated probabilities; and it is invariant to the initial wealth level (and hence not affected by "endowment effects"). In contrast to our approach, previous experiments analyzing diversification behavior either (i) design the choice problems such that only one efficient alternative exists (Rubinstein (2002)), (ii) test if the partition of the choice set affects decisions (Langer and Fox (2004)), without investigating the efficiency of the decisions, or (iii) test the efficiency of subject's portfolio choices using the mean-variance or second-order stochastic dominance (SSD) criterion (Kroll, Levy and Rapoport (1988), Kroll and Levy (1992), and Levy, Levy and Alisof (2004)).[4]

We stress that testing optimality is not our end goal. Given the limited computational ability of the human mind, and the general complexity of the diversification task, it may not be reasonable to expect completely rational choice to begin with, even for our relatively simple tasks. Rather, our objective is to detect patterns in the deviations from optimality in individual portfolio construction decisions, to explain these patterns and to analyze the effect of the framing of the diversification problem.

Our findings are as follows. A large majority of our subjects focus on a subset of the lotteries, where the subsets chosen are consistent with the idea that investors focus on the marginal distribution of the individual choice alternatives. The subjects

[4] Kroll, Levy and Rapoport (1988) and Kroll and Levy (1992) study experimentally the second-order stochastic dominance (SSD) efficiency of portfolio choices when diversifying between three possible risky assets, with different degrees of correlation, and between three risky assets and one riskless asset. Levy, Levy and Alisof (2004) experimentally test the SSD efficiency of portfolio choices when diversifying between one of five to nine possible risky mutual funds and a riskless fund, in order to investigate the homemade leverage decision.

exclude the lotteries that are unattractive when held in isolation, without fully accounting for their possible diversification benefits. Subsequently, many subjects tend to select an equal-weighted combination of the remaining lotteries, and this conditional 1/*n* heuristic is applied even if it is highly irrational in terms of FSD portfolio inefficiency. By contrast, only a few subjects select an even allocation across all lotteries, contradicting the unconditional 1/*n* rule. Consistent with this heuristic behavior, we find that framing has a substantial influence on portfolio construction decisions (similar to the findings of Langer and Fox (2004), and Benartzi, Peleg and Thaler (2007)). Emphasizing the diversification benefits rather than the marginal distribution of the individual choice alternatives improves the decisions considerably. In other words, subjects don't fully appreciate the effect of diversification unless these effects are clearly pointed out to them. Moreover, adding irrelevant alternatives influences portfolio decisions, further suggesting that problem presentation has an important effect on individual portfolio decisions.

The remainder of this study is structured as follows. Section II discusses the experimental design and implementation. Section III discusses our results. Finally, Section IV presents our conclusions.

II. Experimental Design

A. *Lotteries*

Our experiment consists of five main tasks (Task 1-5), each of which contains three or four out of six base lotteries (B_1-B_6), as shown in Table 1.

[Insert Table 1 about here]

Several remarks are in order to explain our research design. First, to limit the cognitive complexity of the choice problems, we focus on a small number of base lotteries and a small number of scenarios. Specifically, the first three tasks use three base lotteries (X_1, X_2 and X_3) with a payoff in three possible scenarios (S_1, S_2 and S_3). Three is the minimum number of lotteries needed to distinguish between the unconditional version of the 1/*n* rule (which yields an even allocation across three base lotteries) and the conditional version (which yields an even allocation across two base lotteries). We need at least three scenarios to avoid perfect linear dependence between the lotteries. The remaining two tasks add one redundant lottery (X_4) to the three main base lotteries, allowing us to investigate the framing effects caused by the addition of irrelevant alternatives.

Second, the subjects may diversify between the three base lotteries. Obviously, this substantially increases the complexity of the problem, because there are infinitely many combinations. To limit this complexity we focus on the convex hull of the base lotteries, or the case where all convex combinations of the base lotteries allowed:

(1) $$W = \left\{ (w_1, w_2, w_3) : \sum_{j=1}^{3} w_j = 1; w_j \geq 0 \;\; j = 1,2,3 \right\}$$

with w_1, w_2 and w_3 for the weights assigned to X_1, X_2 and X_3 respectively. In this setup, negative positions are not allowed (no short sales), the weights must sum to unity (no riskless alternative) and no further restrictions are placed on the weights. Short sales possibilities and the availability of a riskless alternative would substantially increase the complexity and cognitive burden of the choice problem, and are therefore not permitted in our experiment.

Third, to further limit the computational complexity of the diversification task we use equal and moderate probabilities of $\frac{1}{3}$ for every scenario. This approach also helps to reduce the possible effects of probability distortion, but it need not fully eliminate these effects. For example, Cumulative Prospect Theory with the functional specification and parameter values of Tversky and Kahneman (1992) predicts that the lowest (negative) outcome of each lottery is transformed from $\frac{1}{3}$ to 0.35, the middle (positive) outcome to 0.18 and the highest (positive) outcome to 0.34. Importantly, the FSD rule is invariant to subjective transformation of the cumulative probabilities and our inferences based on this criterion are not likely to be affected by probability distortion.

Fourth, to ensure that the experiments resemble real-life investment choices, all base lotteries are "mixed gambles" that involve both gains and losses. Further, no combination of the base lotteries yields only gains. In this way we hope to avoid situations in which subjects take more risk, because they have no possibility to lose money – the "house-money effect." This possible effect is consistent with our use of the FSD criterion (which places no restrictions on risk attitudes), but it would reduce the propensity to diversify and hence lower the power of our experiments.

Fifth, a subject may use the 1/*n* rule or conditional 1/*n* rule simply because the choice alternatives are not sufficiently different given her preferences. For example, a risk-neutral subject will be indifferent between alternatives that yield the same average outcome, irrespective of possible differences in the distribution of the outcomes. To ensure that the allocations have a substantial effect on the probability distribution of the outcomes, and the FSD criterion has discriminating power, the base lotteries are constructed in such a way that they exhibit significant differences in mean, dispersion and ranking of the outcomes in order.

B. Tasks

In Task 1, where $(X_1, X_2, X_3) = (B_1, B_2, B_3)$, Lottery B_3 has an unfavorable marginal distribution; it is FSD-dominated by B_1 since it involves a lower minimum (-75 vs. -50), the same median (+25) and a lower maximum (+50 vs. +125). Also, B_3 has limited value as a diversifier to risk averters, because it has a strong positive statistical association with lotteries B_1 and B_2.

In Task 2, where $(X_1, X_2, X_3) = (B_1, B_2, B_4)$, B_3 is replaced with B_4, which plays an important role in the experiment. B_4 is in fact a permutation of B_3 and these two lotteries have the same marginal distribution. Hence, B_4 is again FSD-dominated by B_1 when held in isolation. Still, B_4 should be of interest to risk averters, because in contrast to B_3 it has a negative statistical association with lotteries B_1 and B_2, yielding possible diversification benefits. Interestingly, B_2 is FSD dominated by the simple combination of investing 75 percent in B_1 and 25 percent in B_4, because it involves the same minimum (-25) and median (0), but a higher maximum (+100 vs. +75) Furthermore, every combination that contains a positive allocation to B_2 is FSD dominated by some combination of B_1 and B_4. Subjects focusing only on the alternatives with attractive marginal distributions are likely to oversee the diversification benefits of B_4 and make inefficient choices.

In Task 3, where $(X_1, X_2, X_3) = (B_1, B_2, B_5)$, B_4 is replaced with B_5, the equal-weighted average of B_1 and B_4, that is, $B_5 = \frac{1}{2}B_1 + \frac{1}{2}B_4$. This merely cosmetic change reduces the choice set by excluding implied allocations to B_4 greater than to B_1, "hides" the unfavorable marginal distribution of B_4, and emphasizes the diversification benefits from combining B_1 and B_4. In fact, B_5 has the same marginal distribution as B_2, but it offers greater diversification possibilities due to the negative statistical association with B_1.

In Task 4 and Task 5, we reframe the portfolio construction problem by adding one simple, but irrelevant alternative to earlier tasks. In Task 4, where (X_1, X_2, X_3, X_4) = (B_1, B_2, B_4, B_6), we add B_6, an equal weighted combination of B_1 and B_2 (that is, $B_6 = \frac{1}{2}B_1 + \frac{1}{2}B_2$), to Task 2. In Task 5, where (X_1, X_2, X_3, X_4) = (B_1, B_2, B_5, B_6), we add B_6 to Task 3. These additions do not alter the choice set and formal choice problem, and should have no influence on choices.[5]

C. FSD Portfolio Efficiency Test

We analyze each subject's choices using the criterion of First-order Stochastic Dominance (FSD) efficiency. A typical problem in gauging the outcomes of choice experiments (as well as real-life choices) is that the preferences of the subjects are not (fully) known or are constructed at the moment of the decision (Payne, Bettman and Johnson (1992), and Slovic (1995)). This makes it difficult to establish if observed diversification behavior is rational and to what degree. The criterion of FSD circumvents this problem, because it does not require a precise specification of the preferences of the decision maker and applies for a broad class of preferences.

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[5] In addition, we presented four additional tasks (Task 6 to Task 9) to the subjects. These tasks test the effect of adding the irrelevant alternative B_7, an equal weighted combination of B_2 and B_3 (that is, $B_7 = \frac{1}{2}B_2 + \frac{1}{2}B_3$), to Tasks 2 to 5. These additions do not alter the efficient choice sets, although some highly inefficient allocations, as compared to Task 3, with more weight assigned to B_4 than to B_1 are made possible. The results of Task 6 to 9 reveal similar behavioral patterns as we find in Task 2 to 5 (see next section). Subjects focus on the marginal distributions, thereby largely ignoring diversification benefits, and divide their money equally between the selected alternatives. Moreover, emphasizing diversification benefits improves choices, while adding irrelevant alternatives deteriorates choices. These tasks and results are omitted here for the sake of brevity. More details are available from the authors upon request.

According to the traditional definition, a choice alternative with cumulative distribution function $F(x)$ FSD dominates another alternative with cumulative distribution function $G(x)$ if and only if $F(x) \leq G(x)$ for all *x* with a strong inequality for at least some *x*. Since FSD only requires that people prefer more over less, it is a minimal requirement for rational behavior, both in expected utility theory and many non-expected utility theories (for example CPT). Descriptively, FSD also appears a valid criterion, because subjects seldom select an alternative that is FSD dominated if the dominance is easily detected, and FSD violations may be regarded as errors rather than genuine expression of preferences (Tversky and Kahneman (1986), and Charness, Karni and Levin (2007)).

To analyze the FSD efficiency of choices we use the recently developed Kuosmanen (2004) and Kopa and Post (2009) mathematical programming tests for determining if a given *portfolio* is FSD efficient relative to all possible portfolios formed from a set of assets.[6] A rational decision-maker has no preference for a specific ranking of outcomes over the various states of the world ceteris paribus. For example, a lottery that yields \$100 when tails are due and \$0 when heads are due FSD dominates a lottery that pays off \$0 when tails are due and \$50 when heads are due. This holds notwithstanding the opposite rankings of both lotteries within each state of the world. More general, Lottery *X* dominates Lottery *Y* by FSD if and only if all outcomes of *X* are larger than or equal to all outcomes of at least some permutation of *Y*. Therefore, the FSD portfolio efficiency tests evaluate not only the outcomes of the chosen allocation, but also the outcomes of all permutations of the chosen allocation.

When applied to our experiment, the FSD efficiency test statistic, or "inefficiency score", for a given allocation (w_1, w_2, w_3) is computed by solving the following mixed integer linear programming problem:

(2) $$\theta(w_1, w_2, w_3) = \max_{\{z_j\}_{j=1}^{3}, \{p_{sj}\}_{s,j=1}^{3}} \frac{1}{3} \sum_{j=1}^{3} \sum_{i=1}^{3} (z_j x_{ij} - w_j x_{ij})$$

[6] In our experiment, with only three scenarios, the two tests are identical. There is, however, a subtle difference between the two tests: Kuosmanen asks if the given portfolio is FSD non-dominated by all alternative portfolios; Kopa and Post ask if the given portfolio is optimal for any non-satiable investor.

$$s.t. \sum_{j=1}^{3} z_j x_{ij} \geq \sum_{j=1}^{3} \sum_{s=1}^{3} p_{sj} w_j x_{sj} \quad i = 1,2,3$$

$$\sum_{s=1}^{3} p_{sj} = 1 \quad j = 1,2,3$$

$$\sum_{j=1}^{3} p_{sj} = 1 \quad s = 1,2,3$$

$$p_{sj} \in \{0,1\}$$

$$\sum_{j=1}^{3} z_j = 1$$

$$z_j \geq 0 \quad j = 1,2,3$$

This problem seeks an allocation (z_1, z_2, z_3) with outcomes that are greater than or equal to the outcomes of the chosen allocation (w_1, w_2, w_3) or some permutation of those outcomes. The outcomes are denoted by $\{x_{ij}\}_{i,j=1}^{3}$ and the permutation of the outcomes is represented by the binary variables $\{p_{sj}\}_{s,j=1}^{3}$. The inefficiency score $\theta(w_1, w_2, w_3)$ has the compelling interpretation of the maximum possible increase in the mean outcome that can be achieved with a combination that FSD dominates the evaluated combination. Thus, if the inefficiency score takes a value of zero, the evaluated combination is FSD efficient; if it takes a strictly positive value, the combination is FSD inefficient.

To illustrate the working of the FSD portfolio efficiency test in the context of our experiment, consider a subject who excludes B_4 from her choice set and divides her money evenly between B_1 and B_2, that is, $(\frac{1}{2}, \frac{1}{2}, 0)$, in Task 2. As shown in Table 2, a combination with $\frac{7}{8}$ allocated to B_1 and $\frac{1}{8}$ to B_4 or $(\frac{7}{8}, 0, \frac{1}{8})$ dominates this combination. In Scenarios S_1 and S_2, the outcomes remain -37.5 and +12.5, respectively. However, in S_3, the outcome increases from +100 to +112.5, leading to a possible increase of the mean of $\theta(\frac{1}{2}, \frac{1}{2}, 0) = 4\frac{1}{6}$. Hence, a subject who applies the conditional 1/*n* rule to lotteries B_1 and B_2 in Task 2 makes an FSD inefficient choice, as she forgoes at least $4\frac{1}{6}$ in terms of mean outcome.

[Insert Table 2 about here]

A remark on computational complexity seems in order here. Testing if a given combination is FSD efficient requires the above mixed-integer programming. In addition, delineating the entire FSD efficient set is complicated by the fact that the efficient set is often not convex; combining two FSD efficient combinations does not always yield an FSD efficient combination. These complications stem from the fact that the subject's preferences are not known to the analyst and that very diverse preferences are admitted under the FSD rule. These issues complicate the testing of FSD efficiency for the analyst, but for the individual subject this problem is less relevant, because only her personal preferences are relevant for her decision and these preferences are known to her. We do not claim that the subject faces a simple problem, but rather that she presumably doesn't apply the FSD rule and restricts her attention to her own preference rather than the entire set of preferences that is admitted by the FSD rule.

D. FSD Efficient Portfolios

Graph A of Figure 1 shows the inefficiency scores ("the maximum possible increase in the mean given risk") for all feasible combinations of w_1 and w_2 in Task 1. The weight w_3 is not shown, because it can be found as the residual $w_3 = 1 - w_1 - w_2$.

[Insert Figure 1 about here]

Despite the generality of the FSD criterion, the efficient set (all combinations with a zero inefficiency score) is only a small subset of the entire choice set. For this task, the efficient set is given by:

(3) $$W_1^* = \left\{ (w_1, w_2, w_3) : \left(w_1 \in \left[\tfrac{1}{5}, 1\right]; w_2 = 0; w_3 = 1 - w_1\right) \cup \left(w_1 \in [0,1]; w_2 = 1 - w_1; w_3 = 0\right) \right\}$$

In other words, investing 20 percent or more in B_1 and the remainder in B_3, or, alternatively, combining B_1 and B_2, is efficient. Full investment in B_1 is clearly efficient as it maximizes the expected pay-off. Some subjects should combine B_1 with B_2, or even invest everything in B_2, to reduce their downside risk. Other subjects should combine B_1 with B_3 to create more upside potential in scenario S_2. However, B_3 has an unfavorable marginal distribution, with the largest loss, smallest gain, and lowest expected value, and a large allocation to B_3 is non-optimal for any subject. Indeed, the lowest inefficiency score is achieved with full allocation to B_3; $\theta(0,0,1) = 33\frac{1}{3}$. Note that B_2 is attractive for a very different preference class than B_3, and mixing B_2 and B_3 is non-optimal for every rational subject. Using the unconditional 1/*n* heuristic of investing an even amount in each alternative $(\frac{1}{3}, \frac{1}{3}, \frac{1}{3})$ is highly inefficient, with an inefficiency score of $\theta(\frac{1}{3}, \frac{1}{3}, \frac{1}{3}) = 16\frac{1}{2}$.

In Task 2, B_3 is replaced with B_4, a simple permutation of B_3. This replacement has an important effect on the efficient set, since it introduces new diversification benefits for risk averters. Graph B of Figure 1 shows the FSD inefficiency scores. We will denote the allocations chosen in Task 2 by y_1, y_2 and y_3 for sake of comparability with later tasks. Specifically, the efficient set in Graph B of Figure 1 is given by:

(4) $$W_2^* = \left\{ (y_1, y_2, y_3) : y_1 \in [\tfrac{1}{8}, \tfrac{1}{4}) \cup [\tfrac{5}{8}, 1], y_2 = 0, y_3 = 1 - y_1 - y_2 \right\}$$

Allocating a non-zero percentage to B_2 now is FSD inefficient. B_3 and B_4 have the same, unattractive marginal distribution and the largest inefficiency score is achieved with full allocation to B_4; $\theta(0,0,1) = 33\frac{1}{3}$. Nevertheless, allocating a small fraction ($y_3 \leq \frac{3}{8}$) or a large fraction ($\frac{3}{4} < y_3 \leq \frac{7}{8}$) to B_4 and the remainder to B_1 is efficient. Due to the negative statistical association between B_1 and B_4, a risk averse subject should now mix B_1 and B_4 rather than B_1 and B_2. Notably, the simple combination of investing 75 percent in B_1 and 25 percent in B_4 yields the same outcomes as B_2 in S_1 and S_2 and a better outcome in S_3 (+100 vs. +75). Full investment in B_2 therefore yields an inefficiency score of $\theta(0,1,0) = 8\frac{1}{3}$ (or 50 percent of the expected payoff of €16.67) in Task 2. Moreover, subjects applying the conditional diversification heuristic to B_1 and B_2 leave €4.17 ($\theta(\frac{1}{2}, \frac{1}{2}, 0) = 4\frac{1}{6}$) on the table, and the unconditional 1/*n* rule yields an inefficiency score of $\theta(\frac{1}{3}, \frac{1}{3}, \frac{1}{3}) = 5\frac{5}{9}$.

Graph C of Figure 1 shows the results for Task 3. In this task, B_4 is replaced with B_5, or the equal-weighted average of B_1 and B_4, that is, $B_5 = \frac{1}{2}B_1 + \frac{1}{2}B_4$. This purely cosmetic change reduces the choice set by excluding allocations to B_4 greater than the allocations to B_1. Moreover, it “hides” the unfavorable marginal distribution of B_4, while stressing the diversification benefits from combining B_1 and B_4 over B_2. For the sake of comparability with Task 2 (Graph B of Figure 1), we will transform the allocations chosen in Task 3 to their implied Task 2 weights; y_1 includes both the direct allocation to B_1 and half of the allocation to B_5. Thus, if $\frac{1}{2}$ is allocated to B_1 and $\frac{1}{2}$ to B_5, we have $y_1 = \frac{3}{4}$.

Compared with Graph B of Figure 1, the most inefficient alternatives, which involve a relatively high allocation to B_4, are now eliminated. The inefficiency score reaches its maximum at $(0,1,0)$ and $(\frac{1}{2},0,\frac{1}{2})$. Indeed, B_2 and B_5 have the same marginal distribution and hence full allocation to one of these two lotteries yields the same inefficiency score; $\theta(0,1,0) = \theta(\frac{1}{2},0,\frac{1}{2}) = 8\frac{1}{3}$. However, B_5 is more attractive for diversification purposes, implying that all combinations with a non-zero allocation to B_2 are inefficient. In addition, large allocations to B_5 ($y_3 > \frac{3}{8}$) are also inefficient. Specifically, the efficient set for Task 3 is given by

(5) $$W_3^* = \left\{ (y_1, y_2, y_3) : y_1 \in [\tfrac{5}{8}, 1]; y_2 = 0; y_3 = 1 - y_1 - y_2 \right\}$$

As before, the unconditional naïve diversification heuristic of investing an even allocation in each alternative $(\frac{1}{3},\frac{1}{3},\frac{1}{3})$ is inefficient for every subject in Task 3, with an inefficiency score of $\theta(\frac{1}{3},\frac{1}{3},\frac{1}{3}) = 2\frac{7}{9}$.

In Task 4 (Task 5), we add the equal weighted combination of B_1 and B_2 (that is, $B_6 = \frac{1}{2}B_1 + \frac{1}{2}B_2$) to Task 2 (Task 3). These additions keep the efficient choice set exactly the same, implying that Equation (4) (Equation (5)) gives the efficient set, formulated in terms of implied Task 2 allocations. For Task 4, the inefficiency scores are shown in Graph B of Figure 1, while the values for Task 5 are shown in Graph C of Figure 1. Similar to Task 2 (Task 3), allocations to B_2 are inefficient in Task 4 (Task 5). In addition, B_6 consist for 50 percent of B_2 and positive allocations to this lottery similarly result in inefficient allocations.

E. *Subjects and Procedures*

In total, 107 third and fourth year undergraduate students of economics and financial economics participated. These students were recruited during advanced courses on portfolio theory or financial economics. At that stage of their studies, the students have completed at least two basic courses in statistics, microeconomics and finance and thus were familiar with formal decision making, probabilistic calculus and portfolio theory. In fact, a formal requirement to participate in these courses is that subjects successfully completed a course on Markowitz portfolio theory.

The Appendix shows the format in which the tasks were presented to the subjects (translated from Dutch to English).[7] Answering the diversification questionnaire took the subjects on average roughly one hour. The choices were filled out on a paper form that could only be handed in after all tasks were completed. Therefore, the choices of previous tasks remained available to the subjects during the course of the experiment. In addition, all subjects brought or received a pocket calculator to help them in performing the necessary calculations.

The test form includes an example to illustrate the objective of the tasks, to emphasize that the percentages should sum to 100 percent, and to illustrate how a chosen allocation affects the distribution of gains and losses. To avoid unintended anchoring effects, the percentages printed on every form were randomized. Further, the test form shown in the Appendix uses a particular ordering for the tasks, lotteries and scenarios. To avoid any unintended ordering effects (for instance, the subjects focusing on the first lottery or losing concentration in the last task), the actual test forms used randomized orderings. An unreported follow-up analysis reveals no significant effects of the example percentages or the ordering of the tasks, lotteries and scenarios.

We use incentive-compatible payoffs. Specifically, the subjects were told that one of the nine tasks is selected at random and played for real money at the end of the experiment. Each task is equally likely to be selected. This incentive scheme has proven to be an effective tool in static decisions problems like ours, since it avoids income effects while the incentives in each task are not diluted by the probability of payout (see Starmer and Sugden (1991), and Cubitt, Starmer and Sugden (1998)).

[7] The original experiment also included Task 6 to Task 9; see Footnote 5. Since our main text does not discuss the results of these tasks, the Appendix also excludes these tasks for the sake of brevity.

Since there is a possibility that subjects would lose money we asked each subject to bring €25 to the experiment. We explicitly stressed this possibility before the start of the experiment, to make sure the subjects were fully aware of this. Also, to cover possible losses, each subject received an attendance fee of €10 and received €15 for participating in another 30 minute questionnaire which took place after the current experiment, a similar procedure as in Ackert, Charupat, Deaves and Kluger (2009).

After each subject completed her tasks, we handled the payments by calling the subjects forward, asking them to put their home brought €25 on table and throwing dices to determine their earnings. Hence, subjects could only lose out-of-pocket money if they were willing to take the risk of loosing more than €25 in an individual task.[8] The average subject took home roughly €50 (≈$75), which in our view is a large amount and incentive for participating in a one-and-a-half hour lasting experiment.

In a preliminary experiment without choice-related monetary incentives, we found many errors of computation, suggesting that the subjects paid less attention without monetary rewards. In this experiment, with monetary rewards, no-one opted not to participate after reading the instructions, made serious miscalculations or did not fill in the amounts allocated to each lottery, leaving us with a final sample of 107 subjects. The experiment reported here actually replaces an earlier, similar experiment in which some of the subjects were randomly selected to play for real money – "between-subject" rather than "within-subject" selection. This incentive scheme was

[8] A possible objection to this incentive scheme is that it may stimulate subjects to invest 100% in B_2 or B_5 to avoid paying out-of-pocket money. The largest possible loss in these lotteries is -€25 and can be paid from the €25 that the subjects earned by participating in the experiment and questionnaire. However, the results in the next section show that only few subjects invest 100% in B_2 or B_5. Hence, most subjects deliberately expose themselves to substantial possible out-of-pocket losses. More importantly, our results are based on the FSD rule, which is invariant to endowments. Notably, in Task 2 (Task 3) B_2 is FSD-dominated by the relatively simple combination of investing 75% in B_1 and 25% in B_4 (50% in B_1 and 50% in B_5). These strategies perform never worse than B_2 and yield a €8.33 (or 50%) higher expected payoff in both tasks. Hence, they are clearly superior to investing 100% in B_2 for subjects who want to avoid out-of-pocket losses.

abandoned, because the perceived incentives may be smaller than originally intended (see Baltussen, Post, Van den Assem and Wakker (2009)). Encouragingly, the earlier experiments lead to the same behavioral patterns and conclusions as reported here.

F. *Statistical Procedure*

Our experimental design involves a series of tasks, each of which replaces or adds one (carefully designed) lottery at a time. Every subject completes the same set of tasks, presented in a randomized order and under a randomized payment scheme. Therefore, our research design allows for pair-wise comparisons between the tasks and the use of elementary statistical methods.

Part of our analysis will employ these pair-wise comparisons. For comparing single proportions between two tasks (for example, the percentage of allocations that are classified as FSD efficient) we will use a simple paired *t*-test for the difference in population proportions. Reassuringly, similar results are obtained when non-parametric Wilcoxon signed-ranked or sign tests are used. For comparing entire allocations, which involves comparing multiple portfolio weights simultaneously, we use Hotelling's paired *T*-squared test (see Hotelling (1947)). Section 2.1 to 2.5 will use these pair-wise comparisons between the tasks.

While pair-wise comparisons are valid in our experiment, more statistical power can be obtained by pooling all tasks and using multivariate regression analysis to jointly analyze the various effects in our experiment. Section 2.6 applies the multivariate regression techniques to the pooled dataset.

III. Results

Table 3 and Figure 2 summarize the chosen allocations in Task 1 to Task 5. In what follows we elaborate on the results of each of these tasks.

[Insert Table 3 about here]

A. Task 1

Table 3 and Graph A of Figure 2 show the results of Task 1 (diversification between B_1, B_2 and B_3). Many subjects allocate 100 percent to B_1 (17.8 percent) or 100 percent to B_2 (28.0 percent). Another large group (38.3 percent) mixes B_1 with B_2. Most subjects (84.1 percent) exclude B_3 from their choice set. Apparently, B_3 is sufficiently unattractive for most subjects to exclude it from their portfolios. Most of the inefficient choices arise due to mixing B_1 with both B_2 and B_3 rather than with either B_2 or B_3. The overall efficiency percentage is high (85.0 percent). Still, due to the generality of the FSD criterion, the efficient choices may include non-optimal choices. For example, the FSD test will always classify the maximizing of the mean (choosing B_1 alone) as efficient, even if diversification is optimal for a given investor.

Only 0.9 percent of the subjects choose the equal-weighted allocation $(\frac{1}{3}, \frac{1}{3}, \frac{1}{3})$ and hence the unconditional 1/*n* rule does not apply here. By contrast, the subjects do exhibit a bias towards the equal-weighted average of B_1 and B_2. Specifically, almost a third (29.2 percent) of the 38.3 percent who mix B_1 and B_2 (or 11.2 percent of all respondents) choose the even allocation $\frac{1}{2}B_1 + \frac{1}{2}B_2$.[9] However, due to this allocation being FSD efficient, we cannot determine if this strategy is irrational, and, if so, to what extent. Overall, a substantial number of subjects focus on two lotteries and divide their money equally between these lotteries (12.1 percent).

Task 2 and Task 3 shed further light on the optimality of and the rationale behind the observed portfolio decisions.

[Insert Figure 2 about here]

B. *Task* 2

In the second task (see Table 3 and Graph B of Figure 2), B_3 is replaced with B_4, leading to $(X_1, X_2, X_3) = (B_1, B_2, B_4)$. Since B_4, in contrast to B_3, has a negative statistical association with B_1 and B_2, this replacement leads to a substantial improvement in the choice possibilities. Thus, we may expect significant changes in

[9] Allocations are classified as "even allocation" if the allocations to each selected alternative fall within a range of 5% around the even allocation, that is, $\left| w_i - (count \{i : w_i > 0\})^{-1} \right| \leq 0.05$.

the allocations. Surprisingly, many subjects seem to overlook the diversification possibilities and they select inefficient portfolios.

A relatively large group (15.0 percent) still allocates 100 percent to B_1. Since this strategy maximizes the expected outcome, this choice remains efficient. In contrast, only a relatively small group (9.3 percent) now allocates 100 percent to B_2. The average allocation to B_2 falls from 54.2 percent to 31.1 percent, while the average allocation to B_1 increases from 42.9 percent to 51.8 percent, resulting in significantly different allocations between Task 1 and Task 2 (p-value = 0.0000). Unlike in Task 1, most subjects choose two or three alternatives (37.4 percent and 38.3 percent). It is remarkable that most of the subjects who choose two alternatives still choose some combination of B_1 and B_2, with no weight assigned to B_4 (18.7 percent of all respondents). Since mixing B_1 and B_2 is inferior to mixing B_1 and B_4, these strategies are now inefficient.[10] Our interpretation for these findings is that the relatively unfavorable marginal distribution of B_4 leads many subjects to exclude this lottery from the choice set, thereby ignoring its possible diversification benefits. In fact, many subjects inefficiently exclude B_4 from their choice set (43.0 percent), while most include B_2 (66.4 percent), supporting this interpretation.

Apart from mixing B_1 and B_2 instead of B_1 and B_4, the subjects also exhibit a strong bias towards the equal-weighted average of B_1 and B_2. Overall, 49.7 percent of the mixtures of B_1 and B_2 are evenly allocated. This is again is a strong indication for a conditional version of the $1/n$ rule. However, the difference with Task 1 is that these choices are demonstrably inefficient, as every allocation to B_2 yields an inefficient choice in Task 2. More evidence for the popularity of the conditional $1/n$ rule is given by the substantial fraction (45.2 percent) of even allocations among the subjects who choose a combination of B_1 and B_4. Of the subjects who invest in two funds, 47.5 percent (17.8 percent of all respondents) choose an even allocation and overall 17.8 percent of the subjects choose an equally weighted allocation among two chosen lotteries. By contrast, only 2.8 percent of the subjects seem to apply the unconditional $1/n$ heuristic.

This remarkable behavior results in roughly three quarters of the subjects (78.5 percent) selecting an FSD inefficient allocation. Recall that the FSD criterion is very

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[10] B_2 is FSD dominated by investing 75% in B_1 and 25% in B_4, which yields a €8.33 (or 50%) higher expected value than B_2.

general (it even allows for "exotic" patterns of risk seeking behavior) and that the true number of non-optimal choices may even be larger than reported here. Moreover, the average inefficiency score is €3.76, meaning that the average subject leaves *at least* €3.76, or 16.7 percent of the expected value, on the table. Given the generality of the FSD rule and the relatively simple structure of the experiment, it is quite surprising that such a large group can be classified as inefficient and make such economically significant mistakes.

As mentioned before, one possible interpretation for these findings is that the relatively unfavorable marginal distribution of B_4 leads the subjects to exclude this lottery from their choice set, thereby ignoring its possible diversification benefits. The outcomes of Task 3 (which replaces B_4 with $B_5 = \frac{1}{2}B_1 + \frac{1}{2}B_4$) in Graph C of Figure 2 further support this interpretation. To interpret Graph C of Figure 2, recall that y_1 includes both the direct allocation to B_1 and half of the allocation to B_5 ($= \frac{1}{2}B_1 + \frac{1}{2}B_4$).

C. Task 3

As explained in Section 1.4, Task 3 uses $(X_1, X_2, X_3) = (B_1, B_2, B_5)$, which reduces the choice options and does not allow for allocations that improve on those available in Task 2. In addition, in Task 2, only few subjects (3.7 percent) assign a higher weight to B_4 than to B_1 and hence choose an allocation that is not feasible in Task 3. Thus, assuming rational behavior, we may expect only minimal differences between the choices in Task 2 and Task 3. Interestingly, the two tasks yield surprisingly different results.

As in Task 1 and 2, a large group (15.0 percent) allocates 100 percent to B_1. Since this strategy still maximizes the expected outcome, this choice remains efficient. However, surprisingly large changes are observed for the remaining subjects. Specifically, compared with Task 2, only a small group (1.8 percent) chooses a combination of B_1 and B_2, with no weight assigned to B_5. The subjects generally reduce their allocation to B_2 and increase their allocation to B_1 (by choosing B_5), clearly suggesting that framing matters. The average implied allocation to B_2 falls from 31.1 percent to 16.9 percent, while the average implied allocation to B_1 increases from 51.8 percent to 65.3 percent, resulting in significantly different allocations between Task 2 and Task 3 (p-value = 0.0000).

Only few subjects (1.8 percent) mix B_1 and B_2, while relatively many (35.5 percent) mix B_1 and B_5. Hence, it seems that emphasizing the diversification advantages of B_4 over B_2, by presenting a reframed version of B_4, makes B_2 look less attractive. The increased number of subjects who completely exclude B_2 from their choice set (from 33.6 percent to 54.2 percent, p-value = 0.0012) gives further support for this. Moreover, only 3.7 percent of the subject ignore B_5 in Task 3, while 27.0 percent ignore B_4 in Task 2 (p-value = 0.0001). By doing so, many of the inefficient allocations that are chosen in Task 2 (and that remain feasible in Task 3) are replaced with efficient choices. In total, the number of inefficient choices decrease substantially from 78.5 percent to 49.5 percent (p-value = 0.0000) and the mean inefficiency score for all subjects reduces to €1.73, or 7.0 percent of the expected value (was 16.7 percent). Also, of the 84 subjects who made inefficient choices in Task 2, only 50 make inefficient choices in Task 3, an improvement of 40.5 percent. By contrast, just three of the 23 subjects make an inefficient choice in Task 3 while making an efficient choice in Task 2.

The observed improvements are quite surprising. Task 3 does not allow for allocations that improve on those available in Task 2 and the allocations that were chosen in Task 2 remain feasible in Task 3. Furthermore, in Task 2, a considerable improvement of the choice possibilities yielded only limited changes. We attribute this remarkable pattern (a minor reaction to a substantial improvement of the choice options and a major reaction to a merely 'cosmetic' change) to the emphasis placed on the favorable diversification benefits rather than the unfavorable marginal distribution. Apparently, the subjects do not fully account for the diversification benefits of the lotteries and focus on the marginal distributions of the lotteries.

The improved efficiency of the portfolios does not mitigate the conditional $1/n$ rule. In fact, a large majority (78.8 percent) of the subjects who mix B_1 and B_5 choose an equal-weighted average. However, unlike the equal weighted combination of B_1 and B_2, this combination is FSD efficient and does not represent irrational behavior. In total, 38.3 percent of the subjects in Task 3 allocate their money evenly among two chosen lotteries. In contrast, only a small fraction of subjects (0.9 percent) choose the equal weighted average of B_1, B_2 and B_5, as the unconditional $1/n$ rule would predict.[11]

A final remark seems in order to value the results of the first three tasks. In Task 1, on average only 2.9 percent weight is allocated to the third asset with the unattractive marginal distribution (B_3). This percentage grows to 17.1 percent in Task 2. While the 14.2 percent increase is roughly the same as the 18.6 percent increase from Task 2 to Task 3 and both increases are statistically significant, the logical inference is very different. In Task 2, an increased allocation to the third asset (B_4) is the predicted, rational response to the improved diversification benefits of this asset. Our focus is instead on the significant allocations to the marginally more attractive, but in this task FSD dominated, second asset (B_2) and the related significant decrease in overall efficiency. Task 3 reframes Task 2 without altering the relevant payoff space. This purely cosmetic change has a similar effect on the allocation to the third asset (B_5) as the fundamental change in Task 2, and significantly improves overall efficiency. Our key result is that a large portion of the subjects focus on the marginal distributions of alternatives and thereby overlook sizeable diversification benefits (in Task 2), unless these benefits are pointed out to them, by showing the marginal distribution of a diversified portfolio (as in Task 3).

D. Task 4

Task 4 adds Lottery B_6 to Task 2, resulting in four choice alternatives instead of three: $(X_1, X_2, X_3, X_4) = (B_1, B_2, B_4, B_6)$. Table 3 and Graph D of Figure 2 show the results. The subjects respond to the additional lottery by shifting away from B_1 and B_2 to B_6. This shift is consistent with our earlier findings for Task 1 to Task 3. Specifically, this is exactly the behavioral pattern that results if subjects focus on the marginal distribution, and dislike alternatives with the most extreme negative attributes as compared to other alternatives, as widely documented in the psychological literature (see for example Simonson (1989), and Simonson and Tversky (1992)); The marginal distribution of B_6 lies in between the marginal

[11] However, HJ note that investors instead tend to choose a 50%-25%-25% over an even allocation when dividing money between three funds. Our findings align with this observation, as respectively 9.3 percent and 6.5 percent select such an allocation in Task 2 and 3.

distributions of B_1 and B_2, B_1 has the most extreme marginal distribution (it has the biggest possible loss), and we observe that preferences move away from this extreme option towards the middle option (B_6).[12]

Nevertheless, B_6 is a combination of B_1 and B_2 and the implied allocations and general level of efficiency are not significantly different from those in Task 2 (p-value = 0.9968). This means that the frequency of inefficient choices remains high (81.3 percent) and many subjects (27.1 percent) overlook the sizeable diversification benefits of B_4, which has an unfavorable marginal distribution. A compelling reason for the insignificant decrease in overall efficiency is the large number of inefficient choices in Task 2, which lowers the statistical power of the contrast with Task 4. From the 23 subjects who make efficient choices in Task 2, seven (30.4 percent) make inefficient choices in Task 4, while only four of the 84 subjects (4.8 percent) who make inefficient choices in Task 2 make efficient choices in Task 4. Moreover, a large fraction of the efficient allocations are risk-neutral choices of full investment in B_1, which are unlikely to be affected by the addition of an alternative with a lower average value. Correcting also for these choices leaves a small group of seven subjects who choose efficient but not risk-neutral combinations in Task 2. Within this group, four subjects (57.1 percent) select inefficient allocations in Task 4. Although the percentages support the notion that adding irrelevant alternatives lowers overall efficiency, the numbers of relevant subjects are simply too small to assign statistical significance to these percentages. Task 5 sheds more light on this issue.

E. Task 5

In Task 5 (see Table 3 and Graph E of Figure 2), we add B_6 to Task 3: (X_1, X_2, X_3, X_4) = (B_1, B_2, B_5, B_6). When we compare the results of Task 5 to those of Task 4, we yet again see that emphasizing diversification benefits helps. Many of the inefficient allocations that are chosen in Task 4 (and that remain feasible in Task 5) are replaced with efficient choices. Most notably, we observe more exclusions of B_2 and B_6 (p-value = 0.1692 and 0.0373) and less inefficient exclusions of B_5 in the

[12] Interestingly, Benartzi and Thaler (2002) obtain similar findings when people are asked to choose between three hypothetical portfolios for their retirement savings investments.

portfolio (p-value = 0.0008). In total, the number of efficient choices increases substantially (31.8 percent vs. 18.7 percent, p-value = 0.0138).

Nevertheless, the 13.1 percent increase is much smaller than the 29.0 percent increase in efficiency between Task 2 and Task 3 (p-value = 0.0022). This reduced effect of emphasizing the diversification benefits is caused by different allocations in Task 5 as compared to Task 3 (p-value = 0.0040). This is quite remarkable, since Task 3 and Task 5 only differ in the addition of a simple and redundant fifty-fifty combination of the first two lotteries, and implies that the addition of irrelevant alternatives changes portfolio compositions. More specifically, more subjects exclude B_1 (29.0 percent vs. 15.9 percent, p-value = 0.0109) from their choice set, reducing the average allocations to B_1 from 65.3 percent to 58.3 percent. By contrast, these subjects tend to select B_6, which is an inefficient alternative because it implicitly includes a 50 percent allocation to B_2. As in Task 4, this is in line with subjects focusing on the marginal distribution, while disliking alternatives with the most extreme negative attributes as compared to other alternatives. The shift from the extreme option (B_1) to the middle option (B_6) significantly reduces the number of efficient choices (31.8 percent vs. 50.5 percent, p-value = 0.0026).

Again, many subjects follow the conditional $1/n$ heuristic, as shown by the large number of subjects who divide their money equally between B_1 and B_4 (85.0 percent). Overall, the favorite number of funds for the subjects is two, of which 78.6 percent divides their money equally between them (compared to 80.4 percent in Task 3). By contrast, relatively few subjects (2.8 percent) follow the unconditional $1/n$ rule.

F. Pooled Statistical Analysis

The analysis so far has focussed on contrasts between pairs of tasks that differ by the change or addition of a single lottery. This allowed us to focus on simple statistical methods. However, by pooling all tasks and using multivariate analysis, we can jointly analyze the results of all our tasks, and obtain more statistical power. We therefore performed a pooled multivariate statistical analysis of all observations of all subjects in Task 1 to Task 5.[13]

We use a probit regression model where the dependent variable is a dummy indicating if a subject made an FSD inefficient choice (with a value of one) or not

[13] We thank an anonymous referee for this suggestion.

(with a value of zero). We try to explain this variable with the following set of regressors:

1. A dummy variable that takes a value of one if the third, “unattractive” gamble has a positive statistical association with the other gambles (“Positive Association”), as is true in Task 1, and else zero;

2. A dummy variable that takes a value of one if a diversified gamble is included to highlight the benefits of diversification (“Framing”), as is true in Tasks 3 and 5, and else zero;

3. A dummy variable that takes a value of one if a fourth, irrelevant gamble is included (“Irrelevant Alternatives”), as is true in Task 4 and 5, and else zero;

To allow for the possibility that the errors of individual subjects are correlated (that is, an error by a given subject in a given task may affect some of that subject’s subsequent choices), we perform a cluster correction at the subject level on the standard errors (see, for example, Wooldridge (2003)).

[Insert Table 4 about here]

The results reported in Table 4 confirm our earlier results obtained from the pair-wise comparisons of tasks. Statistical association has a strong and significant effect. In case of positive statistical association, the probability of inefficiency is 60.5 percent lower than in case of negative statistical association. Framing within the negative association tasks significantly decreases the chance on an inefficient choice by 22.6 percent. Finally, the addition of an irrelevant alternative to the negative association tasks significantly increases the probability of inefficient choice by 8.8 percent.

Logit regression is an obvious alternative to probit regression. Another approach is to use Tobit regression with the inefficiency score (censored between its minimum and maximum population value) as the dependent variable. Comfortably, the results of both alternative approaches are similar in economic magnitude and statistical significance to our probit results. These pooled regression results show that our findings are robust to the statistical method and assumptions used.

G. SSD Portfolio Efficiency

Our analysis thus far has focused on the FSD criterion using the FSD portfolio efficiency test (2). The generality of this criterion sometimes comes at the costs of low discriminating power. Comfortably, power does not seem to be an important issue in our analysis. We have found large percentages of FSD inefficient choices, significantly varying over the tasks between 15.0 percent in Task 1 and 81.3 percent in Task 4. We attribute this power to the design of our lotteries (see Section 1.1) and the relatively large number of subjects in our sample.

Nevertheless, we may analyze individual portfolio choice behavior using the less general efficiency criterion of second-order stochastic dominance (SSD).[14] This criterion makes the additional assumption that decision makers are globally risk averse, a typical assumption in traditional portfolio choice models like Markowitz (1952). Post (2003) develops a simple linear programming test to analyze SSD portfolio efficiency, which we apply to Tasks 1 to 5.

For Task 1, the SSD efficient set is given by $W_1^{**} = \{(w_1, w_2, w_3): w_1 \in [0,1]; w_2 = 1 - w_1; w_3 = 0\}$, which is 44 percent smaller than the FSD efficient set (3). The "complement set" $W_1^{*} \backslash W_1^{**} = \{(w_1, w_2, w_3): w_1 \in [\frac{1}{5}, 1]; w_2 = 0; w_3 = 1 - w_1\}$ contains all portfolios that are optimal for some non-satiable decision maker (FSD efficient) but not optimal for any risk averter (SSD inefficient). While this set is quite large, only 0.9 percent of our subjects choose a portfolio from it – the equal-weighted average of B_1 and B_3. Hence, 15.9 percent of the subjects make an SSD inefficient choice in Task 1, compared with 15 percent using the FSD rule.

For Task 2 and Task 4, the SSD efficient set is given by $W_{2\&4}^{**} = \{(y_1, y_2, y_3): y_1 \in [\frac{5}{8}, 1], y_2 = 0, y_3 = 1 - y_1 - y_2\}$, 25 percent smaller than the FSD efficient set (4). In this case, *no* subject chooses a portfolio from the complement set $W_{2\&4}^{*} \backslash W_{2\&4}^{**} = \{(y_1, y_2, y_3): y_1 \in [\frac{1}{8}, \frac{1}{4}), y_2 = 0, y_3 = 1 - y_1 - y_2\}$, implying that 78.5 percent (81.3 percent) of the subjects make a SSD inefficient choice in Task 2 (Task 4), the same percentages as for the FSD inefficiency.

[14] We thank an anonymous referee for this suggestion.

For Task 3 and 5, the SSD efficient set equals the FSD efficient set, that is, $W^{**}_{3\,\&\,5} = W^{*}_{3\,\&\,5}$, and it is not even possible for subjects to violate the SSD criterion without violating the FSD criterion. Therefore, 49.5 percent (68.2 percent) of the subjects make a SSD inefficient choice in Task 3 (Task 5), again identical to the FSD results. Hence, the two efficiency criteria give very similar results, suggesting that our conclusions are robust to the precise efficiency criterion.

IV. Concluding Remarks

In this paper, we examine the nature and optimality of portfolio decisions and use of diversification heuristics. To get insight in these complex decisions, gauge the optimality of choices, and avoid joint hypothesis problems due to unknown decision maker's preferences, expectations and information sets, we use an experimental approach with well-compensated and financially trained subjects and employ recently developed tests for FSD portfolio efficiency.

Our findings are as follows. A large majority of our subjects seem to focus on the marginal distribution of the individual choice alternatives, while ignoring possible diversification benefits. The subjects tend to exclude the alternatives that are unattractive when held in isolation (that is, alternatives that entail small potential gains and large potential losses), without fully accounting for their possible diversification benefits. In addition, in line with the findings of BT and HJ, many subjects tend to select an equal-weighted combination of the remaining alternatives, a clear manifestation of a conditional 1/*n* rule. This strategy is irrational in then sense that the resulting allocations are FSD dominated, or non-optimal for every rational decision maker. Hence, a large part of the subjects irrationally focus on a subset of choice alternatives and select an equal-weighted combination within that subset.

We also show the importance of the framing of the decision problem. Emphasizing the diversification benefits rather than the marginal distribution of the individual choice alternatives improves decision making. In other words, many subjects don't fully appreciate the effect of diversification unless these effects are clearly pointed out to them. In addition, we show that the addition of irrelevant alternatives changes portfolio allocations. Hence, problem presentation has an important effect on individual portfolio decisions.

Most real-life investment problems are substantially more demanding than the problems presented in our experiment, especially for household investors who are unfamiliar with the computer hardware and software and datasets needed for portfolio optimization. In these situations, the simplifying procedures shown in this study, such as a focus on marginal distributions and a tendency to equal weights, may be even more alluring. Over and above, the natural frame in which individual portfolio problems are presented may further reinforce this; investors can directly observe the marginal distribution of assets, but the statistical association between assets and the associated diversification benefits are less salient and accessible. Evidence supporting narrow framing in real-life investing includes Dorn and Huberman (2010), who show that investors with a discount broker focus mainly on individual asset volatilities instead of the portfolio volatility. In addition, Kumar and Lim (2008), find that household investors tend to frame stock market decisions more narrowly than other investors.

For pension plans, the conditional 1/*n* heuristic may lead participants to focus on a subset of funds in the same, “attractive” asset class. Since diversification effects generally are stronger between asset classes than within asset classes, the resulting allocations may be suboptimal. In this respect, reframing portfolio problems could help improve pension investment choice. For example, pension plans and financial advisors could stress the benefits of diversification between asset classes and including mixed-funds that diversify across multiple asset classes. Hopefully, our study contributes to an increased awareness of diversification heuristics in practice and more attention to problem presentation and decision support.

An irrational focus on marginal distributions may also have market-wide implications. A number of “anomalous” asset pricing patterns naturally emerge if investors care about fluctuations in the individual stocks they hold instead of fluctuations in their portfolio. For example, Barberis and Huang (2001) show that in an economy in which investors are averse to losses and this aversion depends on the outcomes of previous decisions, the focus of individual investors on the outcomes of individual stocks (i.e. the marginal distribution) results in: (i) high returns on value stocks relative to growth stocks (see Fama and French (1992), (1993)), (ii) high returns on the past loser stocks relative to winners (see De Bondt and Thaler (1985), (1987)), (iii) high excess returns on equities (see Mehra and Prescott (1985)), (iv) long term predictability of stock returns (see for example Fama and French (1988)), and (v) excess volatility of the stock prices over their underlying cash flows (see Shiller (1981)). We hope that our experimental results may provide a stimulus for further research along these lines.

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TABLE 1

Lotteries and Tasks of the Experiment

This table summarizes the main tasks and lotteries used in our experiment. Each task involves three or four lotteries (X_1, X_2, X_3 and X_4) with an uncertain payoff in three possible scenarios (S_1, S_2 and S_3) of equal probability (1/3). The lotteries (X_1, X_2, X_3 and X_4) are a selection from six base lotteries (B_1, B_2, B_3, B_4, B_5 and B_6).

	Gain/Loss (€)		
Lottery	S_1	S_2	S_3
B_1	-50	+25	+125
B_2	-25	0	+75
B_3	-75	+50	+25
B_4	+50	-75	+25
B_5*	0	-25	+75
B_6†	-37.5	+12.5	+100

* $B_5 = \frac{1}{2}B_1 + \frac{1}{2}B_4$

† $B_6 = \frac{1}{2}B_1 + \frac{1}{2}B_2$

	Lotteries			
Task	X_1	X_2	X_3	X_4
Task 1	B_1	B_2	B_3	-
Task 2	B_1	B_2	B_4	-
Task 3	B_1	B_2	B_5	-
Task 4	B_1	B_2	B_4	B_6
Task 5	B_1	B_2	B_5	B_6

TABLE 2

Example Illustration of the FSD Portfolio Efficiency Test

A: The FSD inefficient combination $(\frac{1}{2},\frac{1}{2},0)$

	Gain/Loss (€)			
	S_1	S_2	S_3	**Percent**
B_1	-50	+25	+125	50
B_2	-25	0	+75	50
B_4	+50	-75	+25	0
Total	-37.5	+12.5	+100	100

B: The FSD dominating combination $(\frac{7}{8},0,\frac{1}{8})$

	Gain/Loss (€)			
	S_1	S_2	S_3	**Percent**
B_1	-50	+25	+125	87.5
B_2	-25	0	+75	0
B_4	+50	-75	+25	12.5
Total	-37.5	+12.5	+112.5	100

TABLE 3

Summary of Allocations

This table shows the main results of our experiment (107 subjects). For every task, the table shows the average allocations to each alternative, the average implied allocations to B_1, B_2 and B_4, the proportion of subjects who exclude each alternative, the proportion of subjects who invest in one given alternative, the numbers of funds chosen by the subjects, the percentage of equal splits between those funds chosen, the proportion of subjects who rely on a specific diversification heuristic, and the proportion of subjects who chose a FSD inefficient allocation, as well as the Euro and percentage mean inefficiency score over all allocations. For Task 1 to Task 5, w_1 denotes the allocation to B_1 and w_2 denotes the allocation to B_2. For Task 1, w_3 denotes the allocation to B_3, for Task 2 and Task 4, w_3 denotes the allocation to B_4, and for Task 3 and Task 5, w_3 denotes the allocation to B_5. For Task 4 and Task 5, w_4 denotes the allocation to B_6. For the sake of comparability with Task 2, the weights of Task 3 to Task 5 are also transformed to their implied allocations to B_1, B_2 and B_4. The implied allocation to B_1 is denoted by y_1, the implied allocation to B_2 by y_2 and the implied allocation to B_4 by y_3.

	Task 1	**Task 2**	**Task 3**	**Task 4**	**Task 5**
		Average Allocations			
w_1	42.9%	51.8%	47.4%	40.0%	34.4%
w_2	54.2%	31.1%	16.9%	18.9%	17.7%
w_3	2.9%	17.1%	35.7%	17.1%	32.0%
w_4	-	-	-	24.1%	16.0%
		Average implied allocations to B_1, B_2 and B_4			
y_1	-	51.8%	65.3%	52.0%	58.3%
y_2	-	31.1%	16.9%	30.9%	25.7%
y_3	-	17.1%	17.9%	17.1%	16.0%
		Excluded Alternatives			
w_1=0	28.0%	9.3%	15.9%	18.7%	29.0%
w_2=0	18.7%	33.6%	54.2%	45.8%	52.3%
w_3=0	84.1%	43.0%	18.7%	39.3%	23.4%
w_4=0	-	-	-	40.2%	52.3%
		Invested in One Alternative			
w_1=1	17.8%	15.0%	15.0%	12.1%	13.1%
w_2=1	28.0%	9.3%	1.9%	5.6%	1.9%
w_3=1	0.0%	0.0%	3.7%	0.0%	1.9%
w_4=1	-	-	-	1.9%	2.8%
		Number of Funds Chosen			
1 chosen	45.8%	24.3%	20.6%	19.6%	19.6%
2 chosen	39.3%	37.4%	47.7%	30.8%	39.3%
3 chosen	15.0%	38.3%	31.8%	23.4%	19.6%
4 chosen	-	-	-	26.2%	21.5%

Equal Split Between Number of Funds Chosen (as Percentage of Funds Chosen)					
2 chosen	31.0%	47.5%	80.4%	42.4%	78.6%
3 chosen	6.3%	7.3%	2.9%	12.0%	14.3%
4 chosen	-	-	-	32.1%	13.0%
Diversification Heuristics					
Uncond. 1/*n*	0.9%	2.8%	0.9%	8.4%	2.8%
Cond. 1/*n*	12.1%	17.8%	38.3%	15.9%	35.5%
FSD-Efficiency					
Efficient	85.0%	21.5%	50.5%	18.7%	31.8%
Inefficient	15.0%	78.5%	49.5%	81.3%	68.2%
Mean Inefficiency (€)	€1.09	€3.76	€1.73	€3.86	€2.28
Mean Inefficiency (%)	4.7%	16.7%	7.0%	17.2%	9.6%

TABLE 4

Probit Regression Analysis

The table displays the results from a probit regression analysis of the decisions made in our experiment (107 subjects). The dependent variable is the FSD efficiency dummy, with a value of 1 for “Inefficient” and 0 for “Efficient.” We use all subjects’ choices of Task 1 to Task 5. Apart from the maximum likelihood estimates and marginal effects (that is, the change in the likelihood on subjects selecting an inefficient choice) of the regression coefficients, the table reports the log-likelihood (*LL*), McFadden’s *R*-squared, and the number of observations. The *p*-values (within parentheses) are corrected for correlation between the responses of a given subject (subject-level cluster correction). Asterisks are used to indicate significance at a 5% (*), 1% (**) or 0.1% (***) level.

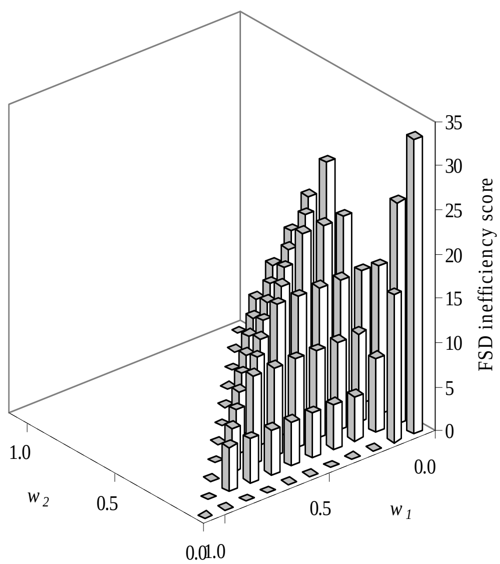
	Coefficient	**Marginal effect**
Positive Association	-1.726***	-60.5%
	(0.000)	
Framing	-0.617***	-22.6%
	(0.000)	
Irrelevant Alternatives	0.315***	8.8%
	(0.000)	
Constant	0.688***	75.4%
	(0.000)	
LL	-294.51	
McFadden R^2	0.189	
No. obs.	535	

FIGURE 1

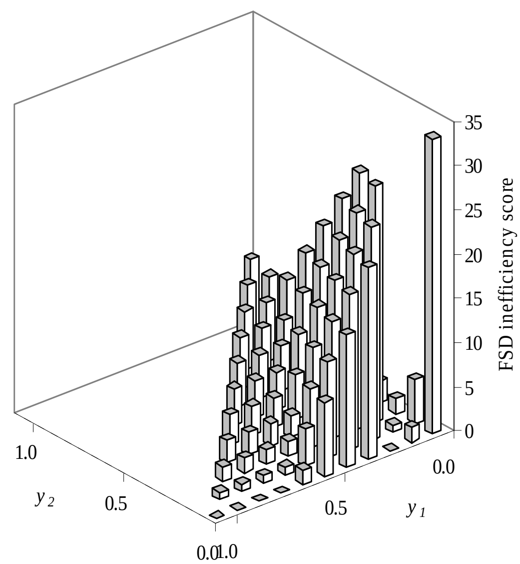
FSD Inefficiency Scores for Task 1 to Task 5

The figure shows the FSD inefficiency score $\theta(w_1, w_2, w_3)$ for all possible allocations in Task 1 to Task 5. The FSD inefficiency score measures the maximum possible increase in the mean outcome that can be achieved with a combination that FSD dominates the evaluated combination. Graph A shows the FSD inefficiency scores for Task 1, Graph B shows the scores for Tasks 2 and 4, and Graph C shows the scores for Tasks 3 and 5. For the sake of comparability with Task 2, the weights of Task 3 to Task 5 are transformed to their implied allocations for Task 2. The implied allocation to B_1 is denoted by y_1, the implied allocation to B_2 by y_2 and the implied allocation to B_4 by y_3. The figure shows all feasible combinations of w_1 (or y_1) and w_2 (or y_2), using 10% intervals. The weight w_3 (or y_3) is not shown, because it can be found as the residual $w_3 = 1 - w_1 - w_2$ (or $y_3 = 1 - y_1 - y_2$).

Graph A: Task 1



Graph B: Task 2 & 4



Graph C: Task 3 & 5

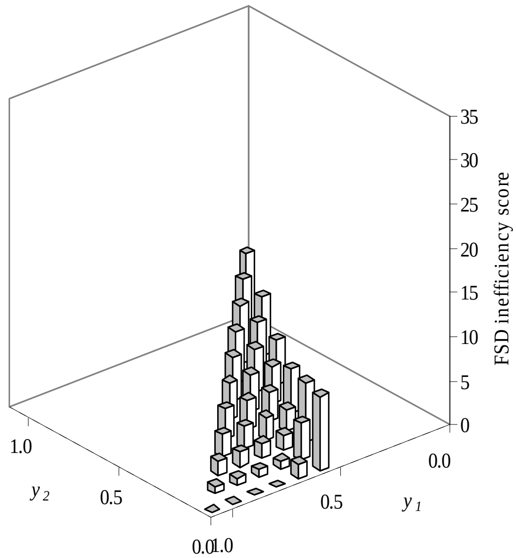
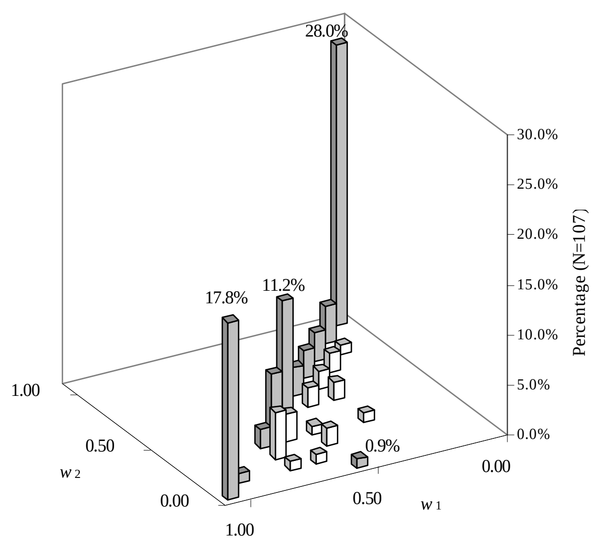


FIGURE 2

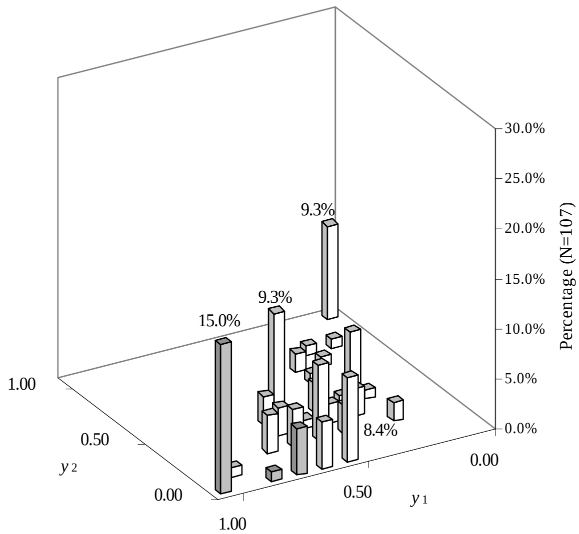
Test Results for Task 1 to Task 5

The figure shows the chosen allocations in Task 1 to Task 5 in Graph A to Graph E. For the sake of comparability with Task 2, the weights of Task 3 to Task 5 are transformed to their implied allocations for Task 2. The implied allocation to B_1 is denoted by y_1, the implied allocation to B_2 by y_2 and the implied allocation to B_4 by y_3. The weight w_3 (or y_3) is not shown, because it can be found as the residual $w_3 = 1 - w_1 - w_2$ (or $y_3 = 1 - y_1 - y_2$). The chosen percentages are first rounded to the nearest multiple of 10%, yielding 11 categories $[0,0.05), [0.05,0.15), \cdots, [0.95,1]$ for the allocation to every lottery. The grey bars indicate FSD efficient choices, while the numbers indicate the main equal-weighted allocations as percentage of all choices.

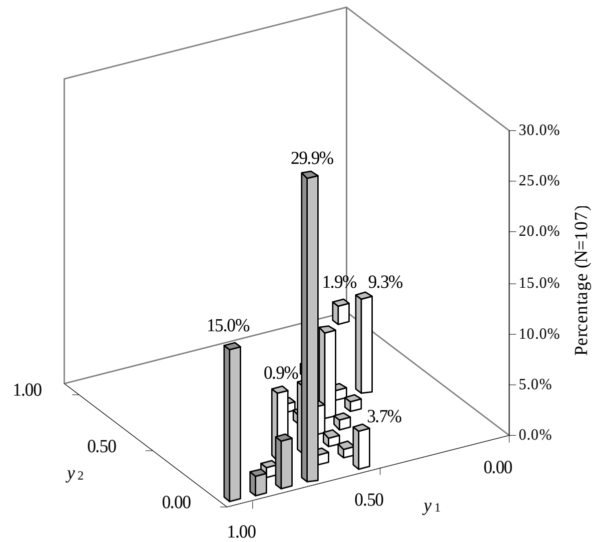
Graph A: Task 1



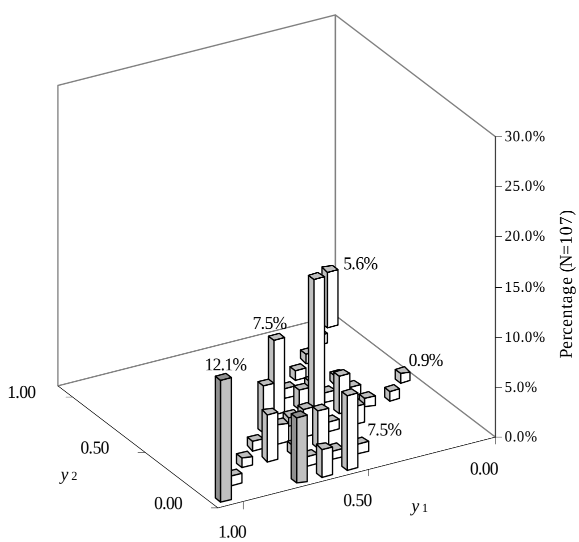
Graph B: Task 2



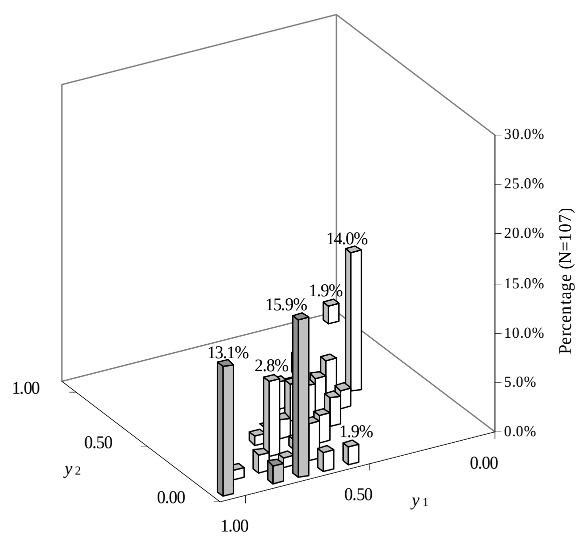
Graph C: Task 3



Graph D: Task 4



Graph E: Task 5



Appendix: The Test Form

EXPERIMENT INVESTMENT AND PORTFOLIO DECISIONS

You are about to participate in an experiment about investment and portfolio decisions. This experiment will last about 60-90 minutes. We will ask you to make investment decisions in nine different situations. By participating in this experiment, it is likely, but not sure, that you will earn real money. The purpose and working of the experiment will be explained below. On the back side of this page, we will explain how the payment procedure is arranged. Please read these two pages with care. If you finished reading them, please wait until we give the sign that you can start fulfilling the nine decision tasks. If you have any questions, please raise your hand.

Purpose of the Experiment: Imagine that you have some money available which you want to invest in financial assets. What would your portfolio of assets look like? How much, and in which assets would you invest? In this experiment, we want you to answer this question in nine tasks. In each task we will provide you with all the necessary information about the investment opportunities that are available on the market. First we will give an example, to clarify the objective of the experiment.

Example You may choose a combination of three lotteries (L_{10}, L_{11} and L_{12}). The lotteries involve a different gain or loss in three different scenarios (S_1, S_2 and S_3). Every scenario has the same probability of occurring (1/3). The table below summarizes the gambles and the gain or loss in each scenario. Please indicate the percentage you would distribute to each lottery in the last column. Negative percentages are not allowed. Also, please fill in the resulting gain or loss of your combination in the last row.

	Gain/Loss (€)			
	S_1	S_2	S_3	%
L_{10}	-200	0	+200	
L_{11}	-100	+100	+300	
L_{12}	+100	-200	+400	
Total				100

Example answer if you decide to distribute 10% to L_{10}, 0% to L_{11} and 90% to L_{12}:

	Gain/Loss (€)			
	$\boldsymbol{S_1}$	$\boldsymbol{S_2}$	$\boldsymbol{S_3}$	**%**
$\boldsymbol{L_{10}}$	-200	0	+200	10
$\boldsymbol{L_{11}}$	-100	+100	+300	0
$\boldsymbol{L_{12}}$	+100	-200	+400	90
Total	+70*	-180	+380	100

* Since the percentages for L_{11}, L_{11} and L_{12} are 10%, 0% and 90% respectively, the outcome in scenario S_1 is (0.10 × -200) + (0 × -100) + (0.90 × +100) = +70.

If the example is clear, please turn to the next page at the backside of this form.

Payment procedure: Your answer to one randomly selected task will be played for real money. Which task will not be known in advance by anyone, but will instead be determined by throwing a ten-sided dice at the end of this experiment. *Hence, remember that which task will be played for real money is completely random, but that you know for sure this task will be one of your played tasks. We do this to encourage you to answer each task as if that one will be played for real money, because each task has the same probability to be played for real money. So we advise you to answer each task as if that task is played for real money for sure.*

After everyone has completed all the tasks you will be asked to come forward, put possible money that you can loose on the table and throw the ten-sided dice. The number that comes up will be the task that you play for real money. . For example, if you throw "3", we will take your answer to Task 3 and play that answer for real money. Throwing a "0" (zero) means "throwing again." Subsequently, you will be asked to throw the dice again to determine which scenario (S_1, S_2 or S_3) is realized. A throw of "1", "2" or "3" means that S_1 is realized, "4", "5" and "6" refer to S_2, and "7", "8" and "9" yield S_3. Anyone who would like to test the dice is requested to raise her hand.

Since we are interested in investment decision making, there will also be a possibility that you lose money. Think of it: investments are almost never without risk. To compensate for these possible losses, each of you will receive €10 for participating in this experiment. In addition, you will receive €15 if you participate in a half-hour questionnaire, which will take place after this experiment. Hence, everyone will receive up to €25 plus the outcome of one randomly selected task. We want to stress that you may end up losing money, but that this only occurs if you want to take the risk. People who are not willing to participate in this experiment are kindly request to raise their hands. After the completion of the experiment, we will handle the payment of your possible earnings.

If you finished reading the instructions, please wait until we give the sign that you can start fulfilling the nine decision tasks. If you have any question, please raise your hand.

Task 1: There are three lotteries (L_1, L_2 and L_3). The lotteries involve a different gain or loss in three different scenarios (S_1, S_2 and S_3). Every scenario has the same probability of occurring (1/3). The table below summarizes the gambles and the gain or loss in each scenario. Which portfolio of these lotteries would you like to hold? Please indicate the percentage you would distribute to each lottery in the last column. Negative percentages are not allowed. Also, please fill in the resulting gain or loss of your combination in the last row.

	Gain/Loss (€)			
	S_1	S_2	S_3	**%**
L_1	-50	+25	+125	
L_2	-25	0	+75	
L_3	-75	+50	+25	
Total				100

Task 2: Now there are the following three lotteries (L_1, L_2 and L_4). The lotteries involve a different gain or loss in three different scenarios (S_1, S_2 and S_3). Every scenario has the same probability of occurring (1/3). The table below summarizes the gambles and the gain or loss in each scenario. Which portfolio of these lotteries would you like to hold? Please indicate the percentage you would distribute to each lottery in the last column. Negative percentages are not allowed. Also, please fill in the resulting gain or loss of your combination in the last row.

	Gain/Loss (€)			
	S_1	S_2	S_3	**%**
L_1	-50	+25	+125	
L_2	-25	0	+75	
L_4	+50	-75	+25	
Total				100

Task 3: Now there are the following three lotteries (L_1, L_2 and L_5). The lotteries involve a different gain or loss in three different scenarios (S_1, S_2 and S_3). Every scenario has the same probability of occurring (1/3). The table below summarizes the gambles and the gain or loss in each scenario. Which portfolio of these lotteries would you like to hold? Please indicate the percentage you would distribute to each lottery in the last column. Negative percentages are not allowed. Also, please fill in the resulting gain or loss of your combination in the last row.

	Gain/Loss (€)			
	S_1	S_2	S_3	**%**
L_1	-50	+25	+125	
L_2	-25	0	+75	
L_5	0	-25	+75	
Total				100

Task 4 Now there are the four lotteries (L_1, L_2, L_4 and L_6). The lotteries involve a different gain or loss in three different scenarios (S_1, S_2 and S_3). Every scenario has the same probability of occurring (1/3). The table below summarizes the gambles and the gain or loss in each scenario. Which portfolio of these lotteries would you like to hold? Please indicate the percentage you would distribute to each lottery in the last column. Negative percentages are not allowed. Also, please fill in the resulting gain or loss of your combination in the last row.

	Gain/Loss (€)			
	S_1	S_2	S_3	**%**
L_1	-50	+25	+125	
L_2	-25	0	+75	
L_4	+50	-75	+25	
L_6	-37.5	+12.5	+100	
Total				100

Task 5: Now there are the following four lotteries (L_1, L_2, L_5 and L_6). The lotteries involve a different gain or loss in three different scenarios (S_1, S_2 and S_3). Every scenario has the same probability of occurring (1/3). The table below summarizes the gambles and the gain or loss in each scenario. Which portfolio of these lotteries would you like to hold? Please indicate the percentage you would distribute to each lottery in the last column. Negative percentages are not allowed. Also, please fill in the resulting gain or loss of your combination in the last row.

	Gain/Loss (€)			
	S_1	S_2	S_3	**%**
L_1	-50	+25	+125	
L_2	-25	0	+75	
L_5	0	-25	+75	
L_6	-37.5	+12.5	+100	
Total				100

Thank you for your cooperation!