# Overweighing Recent Observations: Experimental Results and Economic Implications

Haim Levy* and Moshe Levy**

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* Hebrew University, Jerusalem 91905, Israel. Tel: 972 2 588 3101. Fax: 972 2 588 1341. mshlevy@mscc.huji.ac.il

** Hebrew University, Jerusalem 91905, Israel. Tel: 972 2 588 3219. Fax: 972 2 588 1341. mslm@mscc.huji.ac.il

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## Abstract

We conduct an experimental study in which subjects choose between alternative risky investments. Just as in the "hot hands" belief in basketball, we find that even when subjects are explicitly told that the rates of return are drawn randomly and independently over time from a given distribution, they still assign a relatively large decision weight to the most recent observations - approximately double the weight of the other observations. As in reality investors face returns as a time series, not as a lottery distribution (employed in most experimental studies), this finding may be much more relevant to realistic investment situations than the probability weighing suggested by Prospect Theory and Rank Dependent Expected Utility. The findings of this paper suggests a simple explanation to several important economic phenomena, like momentum (the positive short run autocorrelation of stock returns), and the relationship between recent fund performance and the flow of money to the fund. The results also have strong implications to asset allocation, pricing, and the risk-return relationship.

## INTRODUCTION

Normative economic theory of decision-making under uncertainty asserts how people should behave. Experimental studies dealing with choices under conditions of uncertainty report how people actually do behave when they are faced with several hypothetical alternative prospects. In many cases there is a substantial discrepancy between the observed experimental investment behavior and the normative theoretical behavior. This discrepancy casts doubt on the validity of the theoretical economic models which rely on the normative behavior[1], and may explain several economic "anomalies". This paper experimentally investigates and quantitatively measures individuals' tendency to overweigh recent observations, and analyzes the economic implications of this behavioral phenomenon to capital markets.

The importance of overweighing recent information in capital markets is not new and has been noted by several researchers. Arrow [1982], in the context of a discussion of Kahneman and Tversky's work, highlights

> *"... the excessive reaction to current information which seems to characterize all the securities and futures markets." (p.5)*

De Bondt and Thaler [1985] assert that:

> *"...investors seem to attach disproportionate importance to short-run development" ( p. 794).*

The present paper is an attempt to experimentally quantify this phenomenon, and to estimate some of its economic effects.

[1]Friedman [1953], introduces the "positive economics" concept, asserting that a model is evaluated by its predictive power and not by the validity of its assumptions on agent's rationality. Better models of individual decision making may not improve market level prediction. Whether they improve predictability is an empirical question that experimental economics try to answer, see for example Plott [1986] and Camerer [1995]. In this study we show that investor's overweighing of recent observations can explain observed market price momentum and the flow of money to mutual funds.

The overweighing of recent observations is a special case of the "representativeness heuristic" suggested by Tversky and Kahneman [1974], by which people think they see patterns even in truly random sequences. For example, the pioneering work of Gilovich, Vallone, and Tversky [1985] shows that basketball fans believe that players have "hot hands", meaning that after making a shot a player becomes more likely to make the next shot. This belief is very widely held despite of the fact that it is statistically unjustified (see also Albright [1993] and Albert and Bennett [2001]) . Similarly, Kroll, Levy and Rapoport [1988] study an experimental financial market and show that subjects look for trends in returns even when they are explicitly told that returns are drawn randomly from a given distribution.

Another related issue is that of subjective probability distortion, or the use of decision weights (see Preston and Baratta [1948], Edwards [1953], [1962], Kahneman and Tversky [1979], Tversky and Kahneman [1992], and Prelec [1998]). In most studies related to decision weights, the subjects choose between two options (x, p(x)) and (y, p(y)), but the payoffs, x and y, are not given as time series. Thus, the subjects have to choose between two lotteries, or one lottery and a certain income. Such experiments may be irrelevant for actual investing as, in practice, investors in the market observe rates of return as time series. Therefore, the time dimension may be very important to investors, and thus should be incorporated into the analysis. In the present study, which is relevant for phenomena taken from the capital market, we present the subjects with a choice between two alternatives with given historical time series of returns, ($x_t$) and ($y_t$), where t stands for time (year, month, etc.). Subjects are told that the time series are generated **randomly from fixed distributions**, thus they should rationally attach the same weight to each observation. We test whether they indeed do so, or whether they attach more weight to the recent observations. Thus, we are dealing with the subjective distortion of probabilities as a function of the temporal sequence, not as a function of the probability itself as in the more standard frameworks of decision weights (e.g. Prospect Theory, CPT, or Quiggin's [1982] Rank Dependent Expected Utility (RDEU)), which ignore the temporal sequence.

This paper has three main goals:

(i) To experimentally test whether the most recent observations are overweighed even though the subjects are told that rates of return are i.i.d.

(ii) To estimate quantitatively the magnitude of the decision weights that the subjects attach to the most recent observations.

(iii) To analyze the economic implications of this phenomenon in terms of momentum (the positive autocorrelation of stock returns), the relationship between mutual fund performance and the flow of money to the fund, and in terms of asset pricing.

The structure of the paper is as follows: Section I describes the experiments and provides the results. In Section II we suggest a method of quantitatively estimating the overweighing of the most recent observation. Section III discusses the economic implications of the results. Section IV concludes the paper.

## I. THE EXPERIMENTS AND RESULTS

In order to investigate the importance attached to recent observations we take two approaches. In the first approach we compare the choices of subjects among a set of alternative risky investments under two setups: once when the subjects are given the means and standard deviations of the normal return distributions, and once when instead they are given a time series of the returns on the alternative investments, such that the means and standard deviations are exactly as before. This approach is employed in Experiment I. In the second approach (Experiment II) we provide only the time series of the returns on the alternative investments. All subjects are given the exact same returns, but different subjects get a different time ordering of the returns. In this experiment we test directly whether the order of the returns affect the subjects' choices, i.e., whether they assign a higher decision weight to the most recent observation.

Altogether we have 287 subjects who made 415 choices (128 subjects made two choices each). The subjects are business school students and practitioners in financial markets (financial analysts and mutual funds' managers).

All of the subjects successfully completed at least one statistics course and were familiar with the normal distribution and the concept of independence over time and, in particular, with the random walk. In all the tasks where rates of return are available, the subjects were told that the rates of return were drawn randomly and independently (i.i.d) from fixed normal distributions. Moreover, in all tasks, the subjects were explicitly told that the next realized rate of return (which is relevant for their investment) is drawn randomly and independently from the corresponding normal distribution. These facts were emphasized in the instructions to the subjects.

**Experiment I**

In this experiment we have 128 subjects, 64 of them third-year undergraduate business students and 64 of them mutual fund managers and financial analysts whom we call "practitioners"[2]. All of the subjects had the questionnaire for a relatively long

[2] The experiments reported here are a part of a wider experimental project which also investigates subjects' ability to effectively employ "homemade leverage" in their investments (see Levy, Levy, and Alisof [2003]).

period of time (at least a week), hence, they could make any needed calculation and make the choices without any time pressure.

The experiment, as many other experiments, did not involve any real financial reward or financial penalty to the subjects, which may constitute a drawback. However, Battalio, Kagal and Jiranyakul [1990] have shown that experiments with and without real money differ in the magnitude of the results but not in their essence. Harless and Camerer [1994] have shown that when real money is involved, the variance of the results decreases. Thus, it seems that the absence of money does not drastically change the results.[3] Yet, because no real money was involved one always suspects that the subjects may fill out the questionnaire randomly without paying close attention to the various choices. Fortunately, this was not the case, as shown below.

In this experiment the subjects are requested to complete two tasks. In Task I they are presented with five mutual funds and are told that the return distribution for each of the funds is normal, with given parameters, as presented in Table 1. The subjects are asked the following question: "*Assuming that you wish to invest in only one mutual fund for one year, which fund will you select ?"*.

(Insert Tables 1 and 2 about here)

In Task II the subjects are again asked to choose one of five mutual funds, and again they are told that the return distributions are normal and that returns are independent over time. However, in this task the subjects are given the last 5 annual

[3] Paying a financial reward to the subjects with no financial penalty (which is legally difficult to implement) induces a bias in the results, because the subjects tend to take extreme risks. When you receive a prize for performance and no financial penalty, you probably take a lot of risk, unlike what you do in actual investments. Indeed, when prizes are involved but no potential penalty, the subjects take extremely high leverage (see Kroll, Levy and Rapoport [1988]). When in a similar experiment, the subjects could loose out-of-pocket money, they became net lenders, i.e., shy away from taking risks, see Levy [1997].

return observations of each fund instead of the fund's mean and standard deviation (see Table 2). The returns in Task II are constructed such that the means and standard deviations of each fund are exactly identical to those in Task I.

Results

Table 3 reports the choices in Tasks I and II corresponding to the 5 mutual funds. As there are no significant differences in the choices of the students and the practitioners, we report here only the aggregate results. The main results are as follows:

1) The choices are not random: we test whether the subjects filled out the questionnaire randomly to quickly "get it over with", by employing the Chi-square goodness-of-fit test. To illustrate, in Task I, the subjects had to choose one out of five mutual funds. If the subjects select the fund randomly, we expect on average 128/5 ≅ 26 subjects choosing each fund. Using the observed choices, and the expected number of choices of each fund, we employ the Chi-square goodness-of-fit test with four degrees of freedom. We obtain in Task I a sample statistic of $\chi^2_4$ = 129.3, when the 1% critical value is 13.3. In Task II the sample statistic is $\chi^2_4$ = 100.4. Thus, both the sample statistics are substantially larger than the corresponding critical value, hence regarding each of the two tasks, the hypothesis that the subjects made a random choice is strongly rejected.[4] Thus, it seems that despite the fact that there was no financial reward/penalty, most of the subjects in our experiment made a choice

[4]The chi-square statistic is:

$$\chi^2_{(n-1)} = \sum_{i=1}^{n} \frac{(0_i - E_i)^2}{E_i}$$

, where $0_i$ is the observed number of choices in each category, $E_i$ is the corresponding expected value, n is the number of categories and n-1 is the number of degrees of freedom.

according to their preference and not randomly.

(Insert Table 3 about here)

2) When the return distributions are normal, the mean-variance rule is well known to be optimal under risk aversion (see Tobin [1958]). Moreover, it is also optimal under the Markowitz [1952b] reverse S-shape value function, and it is also necessary under the CPT S-shape value function (see Levy and Levy [2003]). Thus, it is natural to examine the mean-variance efficiency of the subjects' choices. Figure 1 presents the five funds in the mean-standard deviation space. It can easily be seen that funds {D,C,E} are mean-variance efficient and funds {B,A} are inefficient (see Figure 1). The inefficient funds, A and B, together were selected by only 3 out of 128 subjects in both Task I and in Task II.

Thus, we have the encouraging results showing that 98% of the choices are mean-variance efficient. Thus, "framing' the choices in terms of $\mu$-$\sigma$ or in terms of annual rates of return does not affect the percentage of the efficient choices, which remains very high.

(Insert Figure 1 about here)

3) In Task I, the choices were mainly of C and D and not E. Looking at Table 1, we see that Fund E has a little higher expected return than Fund C but much larger standard deviation. It is possible that this risk-return tradeoff induces most of the subjects to select Funds C and D and not Fund E[5].

4) The importance of the time sequence: Because rates of return are i.i.d., theoretically framing the choices in two ways should not affect the choices. This is not the case, because choices have been dramatically changed *within* the efficient set.

[5] Another possible explanation is that even though in this experiment the subjects select only among the mutual funds, it is possible that their knowledge of the real-world riskless interest rate (which was 6%-8% in Israel at the time of the experiment) induced a rejection of Fund E.

While in Task I, choices C and D were very popular, in Task II there is a substantial shift from Funds C and D to Fund E, which became the most popular choice with almost half of the subjects selecting it (compared to less than 11% selecting E in Task I). Focusing on the shifts in choices in Task I and II within the efficient set, we conducted a $\chi^2$ test to examine whether the shifts are significant. We obtain a sample statistic of 44.0 while the 1% critical value is only 13.3, hence the change in choices is highly significant. There is a wide range of possible explanations as to why subjects switched from C and D to E. However, a close look at the rates of return in Table 2 reveals two important characteristics: in four out of five years, E shows a higher rate of return than D, and more importantly, in the last two years the returns on E are better than the returns on D. Though this information is irrelevant under i.i.d. property, it seems that the subjects made use of this information. This experimental finding, i.e., switching to the fund with the highest short-term performance (e.g., the performance in the last two years) conforms with the results of Kroll Levy and Rapoport [1988] and with Arrow's [1982] assertion of an "excessive reaction to current information". Thus, despite of the randomness and independent over time of rates of return, investors switch between funds based on short-term performance.

The comparison of the rate of return on E and C is a little more involved: in two years they have the same rate of return, in two years E is better and in one year C is better (see Table 2). However, in the last year, which probably was more important to the subjects, E is better, even though by only 1%. Thus, the "seemingly" superiority of E over D is stronger than the superiority of E over C, which may explain why a larger shift occurred from D to E than from C to E (see Table 3). Regardless of whether all rates of return affect choices, or only the last one or two observations affect the switch in the choices, one thing is clear: the subjects either misperceive randomness and overweigh recent outcomes, do not believe the i.i.d information or do not believe the normality.

To sum up, the subjects create patterns, and draw conclusions from the irrelevant historical rates of return. This is because, theoretically, under the i.i.d. information, and the data of Tasks I and II, no switch in choices should occur.

Finally, it is possible that in Task II the subjects do not assign relatively large decision weights to the last 1-2 observations, but rather employ some other complicated decision rules, e.g., "select the fund with the highest possible gain and the smallest possible loss" (like fund E), or select the mutual fund based on mean, variance and, say, skewness, though skewness is irrelevant under normal distribution. To address this issue, in Experiment II we refine the analysis regarding the role that recent rates of return play in decision making. This experiment is very simple, and more directly attempts to figure out the role of the most recent observation on the decision making process.

**Experiment II**

The subjects participating in this experiment are 159 undergraduate business school students. The subjects have to choose between only two investment alternatives. As in Task II of the first experiment, the last five returns of each of these alternatives are presented to the subjects, and the subjects are told that the returns are drawn randomly and independently over time from normal distributions. We divide the subject population into two groups, and each subpopulation is given a different version of the questionnaire. One subpopulation is presented with two investment alternatives exactly identical to funds D and E of Task II in Experiment I (see Questionnaire 1 in Table 4). The other subpopulation is presented with the same set of returns for each fund, but the time ordering of the returns are different (see Questionnaire 2 in Table 4). Specifically, Questionnaire 2 is designed such that if more weight is assigned to recent returns Fund D becomes more attractive. Note that if an equal weight of 0.2 is attached to each observation the results in the two questionnaires should be roughly the same. However, if one assigns a relatively large decision weight to the last one or two years, then E is improved relative to D in Questionnaire 1, while D is improved relative to E in Questionnaire 2.

(Insert Tables 4 and 5 about here)

<u>Results</u>

The results of Experiment II are reported in Table 5. Only 29% of the choices were D in Questionnaire 1 versus 45% in Questionnaire 2. A $\chi^2$ test with one degree of freedom reveals that the differences are significant with $\alpha$ = 5%, with a sample statistic of chi-square of 4.35, while the critical value is $\chi^2_{(1,5\%)} = 3.84$. Thus, there is a significant change, albeit not a very strong one, in choices in favor of the fund with the relatively good performance in the last two years. This is so despite the fact that the returns are exactly identical in the two questionnaires. Thus, Experiment II clearly reveals that the last two observations have an important role in determining choices.

We advocate in this paper that probability is distorted in a particular way, emphasizing the last one or two observations. This is in contradiction to the CPT and RDEU probability distortion. For example, by the CPT distortion, probabilities should be distorted in the same way in both questionnaires 1 and 2, overweighing the extreme probabilities of –2% and 45% in Fund E and –5% and 20% in Fund D, regardless of the sequence of appearance of these observations. Therefore, according to CPT the choices should not change across the two questionnaires. This is not the case in our experiment, indicating that the CPT weighing function may be inappropriate for time series returns, as observed in the capital market.

Finally, as not all subjects choose E in Questionnaire 1, and not all subjects choose D in Questionnaire 2, it is obvious that the decision weight assigned to the last 2 observations is less than 100%, and some of the investors may perceive randomness correctly. In many case some complicated decision rules are probably employed. Yet, it is enough that some investors overweigh recent observations to create several important economic phenomena. In the next section we attempt to quantitatively estimate the overweighing of the most recent observation.

## II. Estimating the Decision Weights

In order to analyze the shift in choices and the decision weights applied to the most recent observations one needs to make some assumptions regarding preferences. We start with general assumptions about the preference class (e.g. risk aversion), and then we refine the analysis by employing specific commonly acceptable utility/value functions.

Under the assumptions of normal rate of return distributions and risk aversion, the optimal investment rule which is consistent with von-Neumann and Morgenstern [1953] expected utility maximization is the Markowitz [1952a] mean-variance rule (see Tobin [1958] and Hanoch and Levy [1969]). In this case the mean-variance rule coincides with Second degree Stochastic Dominance (SSD). When rates of return are drawn randomly and independently from normal distributions then the best estimates of the mean and variance are the corresponding sample statistics, assuming each observation has an equal weight of 1/n, n being the number of observations. Our findings imply that in expected utility calculation decision weights, w(p(x)), are employed rather than the objective probabilities, p(x), where w(p(x)) > p(x) for the last one or two observations. In this section, we attempt to estimate w(p(x)). We take two approaches. The first is the Stochastic Dominance approach which allows us to place an upper bound on w(p(x)). In the second approach we assume various typical utility functions and obtain estimates of the median w(p(x)) in the population.

Several studies highlight the importance of overweighing the most recently observed return (see Kroll, Levy and Rapoport [1988], and Chevalier and Ellison [1997]). The results of Experiment I support this view. An increase in the decision weight of the most recent return explains the shift in choices from Funds C and D in Task I to Fund E in Task II. In contrast, the penultimate observation is not overweighed much, because such overweighing would have implied a shift in the choices to Fund B in Task II, a shift which did not occur (in the 4th year, the rate of return on fund B was 34%, much higher than the 15% of fund E, see Table 2). Thus, from the rates of return data and from the specific shift in choices, we conclude that the overweighing of the most recent return is probably the main factor, albeit not the only factor, inducing the shifts in choices observed in our experiments. Therefore, in what follows we analyze the subjects' choices by making the assumption that for the 5th year $w_5(p)>p=0.2$ and for all the other four years $w_i(p)=\frac{1-w_5(p)}{4}<0.2$, where $w_i(p)$ is the decision weights corresponding to year i (i = 1,2,3,4 and 5).[6] As we employ Stochastic Dominance rules in estimating $w_5(p)$, let us first define these rules.

[6]This has been done to make sure that the decision weights like probabilities sum up to 1. This normalization is not necessary to explain the shifts in choices from C to D to E. It is sufficient to assume that the 5th year is assigned a higher decision weight than the other years.

1. Stochastic Dominance Approach

a. Definitions

Consider the funds in Experiment I. When decision weights are employed such that the most recent observation is overweighed Fund E becomes more attractive relative to the other funds. In employing the stochastic dominance approach we ask the following question: what should $w_5(p)$ be such that E will stochastically dominate the other funds? The answer to this question gives an upper bound on $w_5(p)$ , because if all subjects assign a weight equal or greater than this critical value of $w_5(p)$ to the fifth observation, they should all prefer fund E in Task II. We investigate the critical value of $w_5^*(p)$ by employing First and Second degree Stochastic Dominance rules. These decision rules are defined below.

i) *First degree Stochastic Dominance (FSD)*:

Distribution F dominates distribution G for all increasing utility functions if and only if $F(x) \leq G(x)$ for all x, and there is a strict inequality for some value $x_0$. Namely,

$$F(x) \leq G(x) \text{ for all } x \Leftrightarrow E_F U(x) \geq E_G U(x) \text{ for all } U, \text{ with } U' \geq 0 \quad (1)$$

ii) *Second degree Stochastic Dominance (SSD)*:

Define F and G as before, and U is a concave utility function ($U' \geq 0$, $U'' \leq 0$). Then,

$$\int_{-\infty}^{x} [G(t) - F(t)]dt \geq 0 \quad \text{for all } x \Leftrightarrow E_F U(x) \geq E_G U(x) \quad (2)$$

for all U with $U' \geq 0$, $U'' \leq 0$.

Thus, if risk aversion is assumed, SSD can be employed.[7,8] Though we focus in this study on SSD (i.e. risk aversion), experimental studies show that risk-seeking also exists in preferences (see Friedman and Savage [1948], Markowitz [1952b], and Kahneman and Tversky [1979]). In particular, Levy and Levy [2001] show that at least 50% of the subjects are not risk averse. Hence, if preferences other than risk-aversion are assumed, the corresponding Stochastic Dominance criteria should be employed. For example, the Prospect Stochastic Dominance (PSD)[9] rule corresponds to the class of all Prospect Theory S-shape value functions, and the Markowitz Stochastic Dominance (MSD)[10] rule corresponds to the class of all reverse S-shape value functions as suggested by Markowitz [1952b]. Here we focus on risk-aversion and the SSD rule.

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[7] If distributions are normal, the mean-variance rule is identical to SSD, namely

$$\left.\begin{array}{l} E_F(x) \geq E_G(x) \\ \sigma_F(x) \leq \sigma_G(x) \end{array}\right\} \Leftrightarrow E_F\,U(x) \geq E_G U(x) \text{ for all concave } U \Leftrightarrow F \text{ dominates } G \text{ by SSD.}$$

Thus, if the subjects adopt the information given to them regarding the randomness and the normality of distributions of rates of return, they can employ either SSD or M-V rules. However, if the normality is violated due to the employment of decision weights w(p), one can continue to employ (subjective) SSD but the M-V rule loses ground (see Tobin [1958] and Hanoch and Levy [1969]).

[8] In the above two rules we require that there is at least one strict inequality (in both sides of equations ((1) and (2)) to avoid trivial cases. (for the stochastic dominance rules see (Fishburn, [1964], Hadar and Russell, [1969], Hanoch and Levy, [1969], Rothschild and Stiglitz [1970], and Levy, [1992] [1998]).

[9] The PSD rule is as follows: F dominates G for all S-shape utility/value functions, ($U'' \leq 0$ for $x > 0$ and $U'' \geq 0$ for $x < 0$), if and only if

$$\int_y^0 [G(t) - F(t)]\,dt \geq 0 \quad \text{for all } y \leq 0 \qquad \text{and:} \qquad \int_0^x [G(t) - F(t)]\,dt \geq 0 \quad \text{for all } x \geq 0$$

(Once again, we require a strict inequality for some pair $(y_0,x_0)$ and for some $U_0$). A proof of PSD and more detail can be found in Levy [1998].

[10] The MSD rule is as follows: F dominates G for all reverse S-shaped value functions, ($U'' \geq 0$ for $x > 0$ and $U'' \leq 0$ for $x < 0$), if and only if

$$\int_{-\infty}^{y} [G(t) - F(t)]dt \geq 0 \quad \text{for all } y \leq 0 \quad \text{and} \quad \int_x^{\infty} [G(t) - F(t)]dt \geq 0 \quad \text{for all } x \geq 0$$

(With at least one strict inequality). For proof see Levy and Levy [2002].

b. Implementation of the Stochastic Dominance Rules

First, note that Fund E dominates Fund A by FSD with the objective probabilities $p_i = 0.2$ (see Table 2). Any overweighing of the fifth year probability, $w_5>0.2$, does not affect this FSD dominance.

Now let us turn to the more interesting case of Funds D and E, as given in Table 2 (and Questionnaire 1 in Table 4). Figure 2a provides the cumulative distributions of these funds when an equal probability of p = 0.2 is assigned to each observation, as should be done with a random sample composed of five independent observations. As we can see, the two cumulative distributions $F_D$ and $F_E$ intersect, so by equation (1) neither fund dominates the other by FSD.

(Insert Figure 2 about here)

Also, as can be seen from Figure 2a, $\int_{-\infty}^{-2\%}(F_E(x)-F_D(x))dx<0$, hence D does not dominate E by SSD, (see equation (2)) and $\int_{-\infty}^{12\%}(F_D(x)-F_E(x))dx<0$, hence E does not dominate D by SSD. Also, there is no dominance by the Mean-Variance rule. Thus, it is very reasonable that with the objective probability p = 0.2, some risk averters (SSD or Mean-Variance decision makers) will select Fund D and some would select Fund E. Let us now demonstrate how with $w_5(p) > 0.2$, Fund E may be considered better by some risk averters, and beyond some critical value $w_5^*(p)$ Fund E even dominates Fund D by SSD, i.e., should be preferred by *all* risk-averters (SSD dominance).

Assume that $w_5(p) > 0.2$. As the most recent observation is also the smallest return for both funds D and E, this overweighing corresponds to an increase of the first positive area (see Figure 2b) and the negative area decreases (recall that increasing $w_5(p)$ induces a decrease in the other decision weights $w_i(p)$, i = 1,2,3,4). Thus, there is some critical value $w_5^*(p)$ such that the negative area will be equal to the first positive area, hence E will dominate D by SSD. To find the critical $w_5^*(p)$ the following condition must be fulfilled (i.e., equating the first areas enclosed between the two cumulative distributions):

$$w_5^*(p)(-2-(-5)) = \frac{1-w_5^*(p)}{4}\ (12-(-2))$$

or : $\quad 3w_5^*(p) = (1-w_5^*(p))(14/4)$. Hence,

$$12w_5^*(p) = 14-14\,w_5^*(p)$$

which finally yields,

$$w_5^*(p) = \frac{14}{26} = 0.54$$

and the other subjective probabilities are:

$$w_i(p) = \frac{12}{26\cdot 4} = \frac{3}{26} \qquad (\text{for } i = 1,2,3,4)$$

Figure 2b draws the cumulative distributions of E and D with these decision weights, denoted by $F_D^*$ and $F_E^*$. As can be seen from the figure, with the decision weights the negative area is equal to the first positive area (because $(-2-(-5))\cdot \frac{14}{26} = (12-(-2))\frac{3}{26}$). Because all other areas enclosed between the two distributions are positive, we have: $\int_{-\infty}^{x}(F_D^*(t)-F_E^*(t))\,dt \geq 0$, for all x, (with at least one strict inequality for some x), when the superstar emphasizes that these are subjective cumulative distribution with decision weights rather than the objective cumulative distributions, $F_D$ and $F_E$ (compare Figure 2a and 2b). Thus, with $w(p) \geq w^*(p)$, Fund E (subjectively) dominates Fund D by SSD, and all *risk averters* are expected to choose

E. Thus, with risk aversion $w_5^*(p) = 0.54$ is an upper bound on the fifth year decision weight. If all subjects were risk-averse and had $w(p) \geq w^*(p)$, they would all choose Fund E in Task II. As 62 out of the 128 subjects selected Fund E and 34 still selected Fund D, we conclude that either these 34 subjects are not risk averse, or that for these subjects $w_5<0.54$.

Using the same technique in the comparison of Funds C and E, we find that $w_5^*(p) = 0.5$, , i.e., for $0.2 < w_5(p) < 0.5$, some subjects may switch from C to E, and for $w_5(p) \geq 0.5$ all risk averters are expected to shift from C to E. For the sake of brevity, we do not provide the detailed calculation of $w_5^*(p)$ corresponding to C and E.

c. Relaxing the Risk-Aversion Assumption

The Second degree Stochastic Dominance approach is non-parametric, hence does not make assumptions about the specific utility function. This approach provides us with an upper bound on the decision weight in the sense that with risk aversion the experimental results reveal that it is not possible that *all* subjects have $w(p) \geq w^*(p)$. Alternatively, it is possible that not all subjects are risk averters. Thus, in what follows we do not confine ourselves to concave preferences.

c1. PSD and MSD

So far we employ SSD in the comparison of E and D. The experimental results can also be explained with non-concave preferences. Employing MSD and PSD reveals the following results: Fund E dominates Fund D by MSD (for the MSD rule see footnote 10). This dominance holds for the objective probabilities, $p_i = 0.2$, as well as for any overweighing of the most recent observation, $w_5>0.2$. On the other hand, neither E nor D dominate one another by PSD (see footnote 9 for the PSD rule), and this is true both for the objective probabilities and for any overweighing $w_5>0.2$.

Therefore, the results of Table 3 regarding Funds D and E conform either with risk-aversion and an increase in $w_5$, or alternatively, with no overweighing and with about 2/3 of the choices (62 out of 96) conforming with MSD, i.e. with a reverse S-shape value function.

2. Direct Estimation of $w_5(p)$

Assuming a specific utility function enables a direct estimation of $w_5(p)$. Surprisingly, the estimates obtained under different utility functions are very similar, which makes the results quite robust. Below we describe the estimation of $w_5(p)$ under the assumption of a logarithmic utility function, a linear utility function, and the Prospect Theory S-shape value function suggested by Kahneman and Tversky [1992].

In applying the direct estimation approach it is beneficial to employ Questionnaire 2, because here the subjects' choices were split almost evenly between the two funds (see Table 5). This allows us to obtain an estimate of the median $w_5(p)$, as detailed below.

Logarithmic Utility Function

Consider Funds D and E of Questionnaire 2 in Experiment II (see Table 4). What is the value of $w_5(p)$ which makes an individual with logarithmic preferences indifferent between these two funds? The answer is given by the solution to:

$$w_1 \log(W(1-0.05)) + w_2 \log(W(1+0.12)) + w_3 \log(W(1+0.14)) + w_4 \log(W(1+0.12)) + w_5 \log(W(1+0.20)) =$$

$$w_1 \log(W(1-0.02)) + w_2 \log(W(1+0.15)) + w_3 \log(W(1+0.45)) + w_4 \log(W(1-0.02)) + w_5 \log(W(1+0.14))$$

where W is the initial wealth, and $w_i$ is the decision weight of observation i. Recalling that in our framework $w_i = \frac{1-w_5}{4}$ for i=1,2,3,4, and noticing that W cancels out, we have:

$$\left(\frac{1-w_5}{4}\right)\left[\log(0.95)+\log(1.12)+\log(1.14)+\log(1.12)\right]+w_5\log(1.20) \quad =$$

$$\left(\frac{1-w_5}{4}\right)\left[\log(0.98)+\log(1.15)+\log(1.45)+\log(0.98)\right]+w_5\log(1.14),$$

which yields :

$$w_5=\frac{\left[\log(0.98)+\log(1.15)+\log(1.45)+\log(0.98)\right]-\left[\log(0.95)+\log(1.12)+\log(1.14)+\log(1.12)\right]}{\left[\log(0.98)+\log(1.15)+\log(1.45)+\log(0.98)\right]-\left[\log(0.95)+\log(1.12)+\log(1.14)+\log(1.12)\right]+4(\log(1.2)-\log(1.14))}$$

or:

$$w_5=0.44.$$

Suppose that different individuals with this specific type of preferences overweigh the fifth observation differently. Any individual with log utility who assigns a weight higher than 0.44 to the fifth observation prefers Fund D over E, and any individual who assigns a weight lower than 0.44 to the fifth observation prefers Fund E. Assuming a logarithmic utility function, the fact that approximately half of the subjects chose Fund D and half chose Fund E (see Table 5) implies that the median $w_5$ in the population is approximately 0.44.[11]

Linear Utility

A similar analysis under the assumption of linear utility (risk neutrality) leads to:

$$\left(\frac{1-w_5}{4}\right)\left[0.95+1.12+1.14+1.12\right]+w_5 1.20 \quad =\left(\frac{1-w_5}{4}\right)\left[0.98+1.15+1.45+0.98\right]+w_5 1.14$$

Rearranging we obtain:

$$(1-w_5)\left(\frac{4.56-4.33}{4}\right)=(1.20-1.14)w_5,$$

which yields $w_5$=0.49.

[11] Note that a similar analysis of Questionnaire 1 is meaningless in this case, because E is preferred over D for log utility with the objective probabilities, and overweighing the recent return in Questionnaire 1 only makes E even more attractive relative to D. This is true in the cases of linear and Prospect Theory preferences as well.

Prospect Theory Value Function

Tversky and Kahneman [1992] suggest that preferences are described by the following value function:

$$V(x) \quad = \quad \begin{cases} x^{\alpha} & \text{if } x > 0 \\ -\lambda(-x)^{\beta} & \text{if } x < 0 \end{cases}$$

where x is the change in wealth, and $\alpha, \beta$, and $\lambda$ are constants which Tversky and Kahneman experimentally estimate as: $\alpha = 0.88$, $\beta = 0.88$, and $\lambda = 2.25$. With this value function, an indifference between Funds D and E implies:

$$\left(\frac{1-w_5}{4}\right)\left[-2.25(0.05)^{0.88} + (0.12)^{0.88} + (0.14)^{0.88} + (0.12)^{0.88}\right] + w_5(0.20)^{0.88} \quad =$$

$$\left(\frac{1-w_5}{4}\right)\left[-2.25(0.02)^{0.88} + (0.15)^{0.88} + (0.45)^{0.88} - 2.25(0.02)^{0.88}\right] + w_5(0.14)^{0.88} \quad .$$

Rearranging we obtain:

$$(1-w_5)(0.1349 - 0.0814) = (0.2426 - 0.1773)w_5$$

or: $w_5$=0.49.

Thus, under different utility functions we obtain similar estimates for $w_5$, in the range 0.44-0.49.[12] These values are also close to the upper bound $w_5$=0.54 obtained in the Stochastic Dominance approach (and, again, recall that the upper bound states that it is not possible for *all* risk-averse subjects to exceed the bound). The overweighing we find is quite substantial - the decision weight is more than twice the objective probability! In the next section we discuss the economic implications of this phenomenon.

[12] Assuming the Markowitz reverse S-shape value function also yields similar results: taking

$$V(x) \quad = \quad \begin{cases} x^{\alpha} & \text{if } x > 0 \\ -\lambda(-x)^{\beta} & \text{if } x < 0 \end{cases}$$

with $\alpha = \beta = 1.1$ yields $w_5$=0.54.

## III. Economic Implications

The experimentally observed overweighing of recent observations can provide a simple explanation for several phenomena observed in the capital market, and can induce substantial mispricing of financial assets. In this section we discuss some of these implications.

**a. Mutual Fund Performance and the Flow of Money to Funds**

Several researchers have demonstrated that the performance of mutual funds does not exhibit statistically significant trends. Sharpe [1966] finds that a high performance of a mutual fund in one period does not increase the probability of a high performance in the next period. Beckers [1997] also finds that luck is the major factor explaining mutual fund performance. Samuelson [1989] who advocates market efficiency asserts:

> "*Those lucky money managers who happen in any period to beat the comprehensive averages in total return seem primarily to have been merely lucky. Being on the honor roll in 1974 does not make you appreciably more likely to be on the 1975 honor roll.*" (Samuelson [1989] p.4).

Yet, despite of these findings Chevalier and Ellison [1997] have shown that a relatively high performance of a fund in the recent period (recent 1−2 years), increases the inflow of cash to the fund (see also Agarwal, Daniel and Naik [2003], Luo [2003], and Sapp and Tiwari [2003]). Thus, there is a positive relationship between flow and performance, even though the empirical studies reveal that mutual funds managers do not have "timing" and "selectivity" ability, and performance is rather random.

The overweighing of recent returns provides a very simple explanation for this phenomenon. It seems that investors attach a high weight to the most recent returns of funds, and tend to classify funds with relatively high recent returns as "good", although this is statistically baseless. Thus, investors' money "chases" the funds that have the best recent returns, even though this is economically unjustified and creates inefficient allocations and unnecessary transactions (and transaction costs).

**b. Momentum and Price Reversals**

The common belief for years, at least among academics, was that the market is efficient and, in particular, that past rates of return cannot be employed to earn abnormal profit (weak form efficiency, see Fama [1970], [1991]). Recent studies question this assertion. It has been found that for short lags (6−12 months) there is a positive return auto-correlation, and for longer term lags (3−5 years) there is negative return auto-correlation.[13]

The significant auto-correlation of rates of return implies some predictability of stock returns, and thereby challenges the notion of weak market efficiency. Jegadeesh [1990], Jegadeesh and Titman [1993], and Levy and Lim [1998], investigate whether exploiting the return auto-correlations can lead to significant abnormal returns. The results are mixed: Jegadeesh, and Jegadeesh and Titman find that significant abnormal returns are attainable, while Levy and Lim find that there are no abnormal returns after transaction costs.

Several researchers have suggested various different explanations for the pattern of return autocorrelations[14]. The overweighing of recent returns offers a simple explanation for the return autocorrelation pattern. To see this, consider the

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[13]For the empirical findings of auto-correlation see De Bondt and Thaler [1985], [1987], Chopra, Lakonishok and Ritter [1992], Jegadeesh and Titman [1993], Daniel [1996], Fama and French [1988], Poterba and Summers [1988].

[14] See De Bondt and Thaler [1985], Shefrin and Statman [1985], Poterba and Summers [1998], Lo and MacKinlay [1990], De Long, Shleifer, Summers and Waldmann [1990] Wang [1993], Barberis, Shleifer, and Vishny [1998] , Hong and Stein [1999], and Daniel, Hirshleifer, and Subrahmanyan [1999].

following oversimplified example. Suppose that there are two assets with i.i.d random normal returns: x ~ N ($\mu_1$, $\sigma_1$) and y ~ N ($\mu_1$, $\sigma_2$). For simplicity, assume that $\mu_1 = \mu_2$ and $\sigma_1 = \sigma_2$. Thus, without misperception of randomness, the future returns are i.i.d.. Now, suppose that $x_t$ = -10% and $y_t$ = +5% where t is the most recent observation. If investors believe the i.i.d. property of rates of return, the next rate of return will be indeed random. However, this is not the case with an overweighing of recent observations and a misperception of randomness. The relatively large decision weight assigned to the most recent observation will induce some of the investors to sell x and to buy y, which by itself would create a negative rate of return for x and a positive rate of return on y, creating further excess supply for x and demand for y, and so forth. Thus, the overweighing of recent returns may create a positive feedback loop leading to the empirically observed short-term momentum.

This momentum, however, cannot continue forever. Because the firms' earnings and dividends are not affected by investors' perceptions, the dividend component in the rate of return becomes smaller as the price becomes higher. Namely, if the momentum continues for a long period of time, the price of y will be very high, the dividend component in the rate of return will be relatively small and the rate of return will tend to decrease. A price reversal may therefore be obtained, again, reinforced by the positive feedback induced by the overweighing of recent returns (and the exact opposite happens to asset x). Thus, the short-term momentum is followed by a longer-term reversal, explaining the empirically observed U-shaped-auto-correlation pattern[15].

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[15]If returns are drawn randomly, but the investors have some beliefs which are based on the last few observations (bounded rationality), some non-random returns may be created. Based on this behavior, Levy, Levy and Solomon [2000] develop a decision-making model, where only past data is employed by investors as a predictor of future distributions of rates of return. This model induces price behavior with booms and crashes in the stock market. In addition, stock price momentum and stock price reversals are obtained. In this paper we test this behavior experimentally, in an ideal setting where the

**c. Asset Allocation, Pricing, and Beta**

The overweighing of recent returns as experimentally estimated in this paper has a dramatic effect on asset allocation, asset pricing, and the risk-return relationship. To illustrate this claim we perform the following analysis. We randomly select 10 stocks from the CRSP database, and record the last five annual returns on these stocks. Then, based on the objective probabilities (with a an equal weight of 0.2 for each observation) we calculate the objective means, standard deviations, and covariances, and calculate the mean-variance optimal portfolio of these assets based on the objective probabilities.[16] Next, we repeat this analysis, but this time with decision weights as we find in our experiment. We assign a decision weight of $w_5$=0.45 to the most recent observation (somewhere in the middle of the range that we estimate for $w_5$ in section II), and $w_1=w_2=w_3=w_4=0.55/4$. We recalculate the means, standard deviations, and covariances, and the optimal mean-variance portfolio based on these decision weights. To measure the effect of the decision weights on asset allocation and pricing we compare the portfolio weight of each of the assets in these two optimal portfolios and report the relative difference:

$$\Delta_i \equiv \frac{x_i^{dw} - x_i^{ob}}{x_i^{ob}} \qquad (3)$$

where $x_i^{ob}$ is the proportion of asset i in the objective optimal portfolio, and $x_i^{dw}$ is the proportion of asset i in the optimal portfolio based on decision weights.[17]

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subjects are told that rates of return are i.i.d. In addition, we assume increasing vector of decision weights rather than focusing on a subset of rates of return and ignoring all other previous rates of return.

[16] Assuming an annual risk-free rate of 3%.

[17] In this optimization we assume no shortselling, and we report Δ only for those assets with $x_i^{ob} \neq 0$.

We repeat this procedure for 100 independent samplings of 10 stocks to obtain 1000 observations of $\Delta$. Figure 3 shows the distribution of $\Delta$. The mean absolute deviation is 63% ($E|\Delta| = 0.63$). This average absolute deviation of 63% in portfolio weights implies an average absolute deviation of 63% in asset pricing! Thus, it is evident that the overweighing of the most recent return induces substantial deviations in asset allocation and pricing. These deviations correspond to large economic inefficiencies and utility loss. Let us turn now to the effect of overweighing recent returns on the risk-return relationship.

(Insert Figure 3 about here)

The Sharpe [1964]-Lintner [1965] CAPM risk-return relationship is given by:

$$\mu_i = r + (\mu_m - r)\beta_i \tag{4}$$

where $\mu_i$ is the expected return on asset i, r is the riskless interest rate, $\mu_m$ is the expected return on the market portfolio, and $\beta_i$ is the risk of asset i. The empirical test of the CAPM is given by:

$$\overline{R}_i = \gamma_0 + \gamma_1\hat{\beta}_i + \varepsilon_i \tag{5}$$

where $\overline{R}_i$ is the empirically measured average return, and $\hat{\beta}_i$ is empirically measured beta, both of which are calculated with ex-post data. If the CAPM precisely holds and there are no sample errors we expect to find a perfect fit with $R^2$=100% in the regression given by eq.(5). Moreover, Roll [1977] shows that in an empirical study where beta is calculated against *any ex-post* mean-variance efficient portfolio (with short-sells), eq.(5) yields a perfect fit. Unfortunately, most empirical tests reveal a relatively low $R^2$, which implies either a rejection of the CAPM, or that the *ex-post* market portfolio employed is not mean-variance efficient. We show below that the overweighing of recent observations may induce the empirically observed deviation from the CAPM. If investors overweigh recent observations when making their investment decisions, but the econometrician who tests the CAPM assigns an equal weight of 1/n to each observation (where the number of observations is n), a dramatic reduction in the $R^2$ of regression (5) is obtained. Moreover, the reduction in $R^2$ is obtained even if the market portfolio employed is mean-variance efficient. Let us elaborate.

Consider the case where there are n *ex-post* return observations on each asset. Let us denote the average return on asset i calculated with a weight of 1/n for each observation by $\overline{R}_i^{ob}$, were the superscript ob stands for objective probability. Similarly, let us denote the optimal mean-variance portfolio calculated with the 1/n weights by $R_m^{ob}$, with average return $\overline{R}_m^{ob}$, and let us denote the betas calculated against this portfolio by $\beta_i^{ob}$. If recent observations are overweighed, these parameters and the optimal mean-variance portfolio will be different. We denote the corresponding values by $\overline{R}_i^{dw}$, $R_m^{dw}$, $\overline{R}_m^{dw}$ and $\beta_i^{dw}$, where dw stands for the decision weights implied by overweighing the recent observations. We would like to emphasize that if overweighing occurs the investment proportions are affected, and $R_m^{dw}$ would be the observed, as well as optimal market portfolio.

The researcher who tests the CAPM typically employs the 1/n weights, and will therefore employ $\overline{R}_i^{ob}$ in testing the CAPM. She will also use the equal weights to calculate beta, but this beta will be different from $\beta_i^{ob}$, because it is calculated against the market portfolio $R_m^{dw}$; we denote this beta by $\beta^*$. Thus, the empirical research community tests the CAPM with the following regression:

$$\overline{R}_i^{ob} = \gamma_0 + \gamma_1\beta_i^* + \varepsilon_i, \qquad (6)$$

and will not obtain a perfect fit. Hence, even though $\beta_i^*$ is calculated against $R_m^{dw}$, which is mean-variance efficient, unlike the case of Roll [1977], we will obtain in testing (6) $R^2<1$, and the CAPM may be erroneously rejected[18].

Thus, the experimentally observed overweighing of recent observations may have a dramatic impact on the risk-return relationship. In order to examine the magnitude of this effect we randomly select 10 stocks from the CRSP dataset and calculate the means, standard deviations, and covariances based on the last five annual returns of these stocks with the objective weights of $p_i=0.2$. Then, we calculate the optimal mean-variance portfolio $R_m^{ob}$ (again assuming $r_f=3\%$), and we calculate the betas of the 10 stocks (relative to this optimal portfolio), $\beta_i^{ob}$ . Figure 4 depicts the risk-return relationship between beta and the expected return, and, of course, as shown by Roll [1977], the analysis with the objective probabilities leads to the well-known linear Security Market Line (SML) relationship (squares in Figure 4).

Next, using the above argument, we analyze the risk return relationship with the experimentally observed overweighing of the most recent return observation, namely with $w_5=0.45$. Given these decision weights we find a new optimal mean-variance portfolio, $R_m^{dw}$, and calculate the betas relative to this portfolio. Though we use $R_m^{dw}$ the means and betas ($\beta^*$) are calculated with the objective probabilities, as an econometrician would have empirically measured them, and the effect on the risk-return relationship comes only from the change of the optimal portfolio due to the decision weights. The risk return relationship with overweighing is given by the circles in Figure 4. As can be seen in the figure, when decision weights are employed the expected return is no longer a linear function of beta, and $R^2$ is reduced from 1 to

[18] Obviously, if one uses the decision weights employed by the investors she will obtain a perfect fit with $R^2=1$.

only 0.43. It is also interesting to note that the regression line in this case, denoted by $SML^*$ (see dotted line in Figure 4), has a smaller slope and a higher intercept than the SML. This result is typical of the empirical tests of the CAPM, and warrants further investigation.

While the above exercise is for illustration only, it shows the dramatic effects of overweighing recent observations on the risk-return relationship. This overweighing may provide a new explanation for the low $R^2$ obtained in many empirical studies of the CAPM risk-return relationship. The common explanation in the finance literature for the results of empirical tests of the CAPM is that the market portfolio is simply inefficient. Here we show that even with a mean-variance efficient market portfolio the different probabilities employed by the investors and the econometrician can explain the empirically observed low $R^2$.

(Insert Figure 4 about here)

## IV. CONCLUDING REMARKS

We experimentally test the overweighing of recent return observations in an investment experiment with 287 business school students and financial practitioners. We find that it is mainly the most recent observation which is overweighed, and that this overweighing is very strong – we estimate the decision weight attached to the most recent observation as approximately twice the objective probability.

In this framework probabilities are subjectively distorted based on the temporal sequence of the observations, rather than the value of the objective probabilities (as in PT, CPT, and RDEU models). This framework is applicable to circumstances where individuals are given observations as time series, as in financial markets, rather than a "given" set of outcomes and probabilities, as in many decision-making experimental setups.

Our results are consistent with the "hot hand" belief of basketball fans, even though the hot hand phenomenon is statistically baseless (see Gilovich, Vallone and Tversky [1985], and Camerer [1989]). The results are also in line with the findings of Kroll, Levy and Rapoport [1988], who show that subjects make significant changes in their choices based on the two most recently observed rates of return, even though the subjects knew that the returns are drawn independently over time. The results can not be explained by the probability distortion suggested by CPT and RDEU, where the probability distortion is a function of the rank of the outcome, rather than its temporal sequence.

One may argue that if the return distributions are non-stationary it is rational to attach a higher weight to more recent observations. Indeed, this logic may be the origin of the phenomenon we observe. However, we find that individuals attach more weight to recent observations even in circumstances where this is completely unjustified – like in our experiment where the subjects are explicitly told that the distributions are stationary and returns are i.i.d. . Another example is manifested by the empirical observation of a flow of money to mutual funds with good recent performance, even though future performance has been shown to be unrelated to past performance.

There seem to be many important economic implications of this phenomenon. For example, money pointlessly "chases" the funds with the best recent performance, leading to inefficient allocations and to unnecessary transaction costs. Another phenomenon which can be straightforwardly explained by the overweighing of recent returns is the short-term momentum and longer-term reversal of stock returns. The overweighing of recent returns is also shown to lead to significant deviations from "objective" pricing. A simple analysis we perform based on the experimentally estimated overweighing leads to an average absolute deviation of 63% from the objective pricing. Thus, it seems that the heuristic of assigning more weight to more recent observations may lead in many realistic circumstances to bad economic decisions and to large economic inefficiencies.

Finally, the cornerstone risk-return relationship in the finance literature is the Sharpe-Lintner CAPM. Unfortunately, most empirical tests reveal a relatively low $R^2$ between $\overline{R}_i$ and $\beta_i$, with only partial support for the CAPM. Roll [1977] has shown that even with *ex-post* data $R^2$=1, as long as beta is calculated against a mean-variance efficient portfolio. We show that the empirically observed overweighing of recent observations implies a drop of $R^2$ from 100% to only 43%, even when betas are calculated against a mean-variance efficient portfolio. This result is induced by the fact that the mean-variance efficient portfolio (and hence the market portfolio) is determined by the subjective decision weights, while the average returns and betas are calculated assigning an equal probability of 1/n to each observation – as it is done in almost all empirical studies which test the CAPM.

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**Table 1: Means and Variances of Returns in Experiment I Task I**

Fund

| Fund | A | B | C | D | E |
|---|---|---|---|---|---|
| Mean | 12.40% | 10.40% | 12.60% | 10.60% | 14.00% |
| Standard Deviation | 18.87% | 15.82% | 13.15% | 8.33% | 17.17% |

**Table 2: Annual Rates of Return in Experiment I Task II**

Fund

| Year | A | B | C | D | E |
|---|---|---|---|---|---|
| 1 | 14% | 14% | 14% | 12% | 14% |
| 2 | 45% | 18% | 35% | 20% | 45% |
| 3 | -10% | -10% | 2% | 14% | -2% |
| 4 | 15% | 34% | 15% | 12% | 15% |
| 5 | -2% | -4% | -3% | -5% | -2% |

**Table 3: Results of Experiment I**

| Fund | Task I | Task II |
|---|---|---|
| A | 3 | 1 |
| B | 0 | 2 |
| C | **45** | **29** |
| D | **66** | **34** |
| E | **14** | **62** |
| Total | 128 | 128 |

**Table 4: Experiment II**

| | Questionnaire 1 | | Questionnaire 2 | |
|---|---|---|---|---|
| Year | D | E | D | E |
| 1 | 12% | 14% | −5% | −2% |
| 2 | 20% | 45% | 12% | 15% |
| 3 | 14% | −2% | 14% | 45% |
| 4 | 12% | 15% | 12% | −2% |
| 5 | −5% | −2% | 20% | 14% |

**Table 5: Results of Experiment II (in percent)**

| Questionnaire 1 (n=66) | | Questionnaire 2 (n = 93) | |
|---|---|---|---|
| D | 29% | D | 45% |
| E | 71% | E | 55% |
| Total | 100% | Total | 100% |

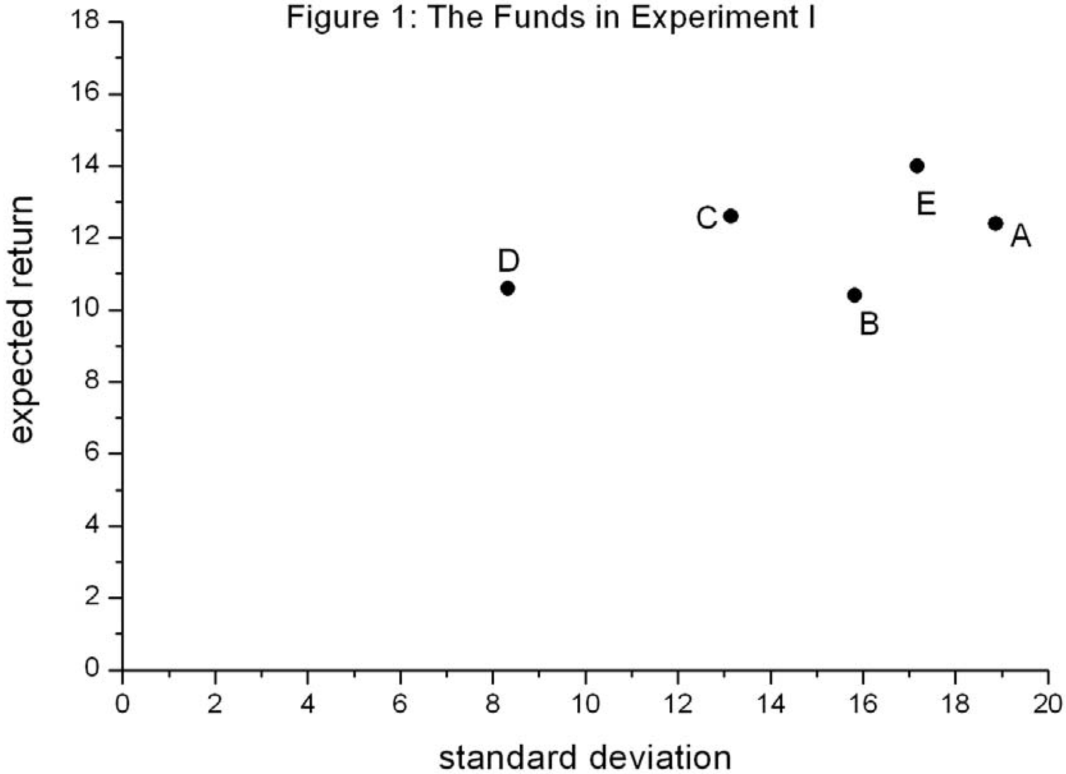
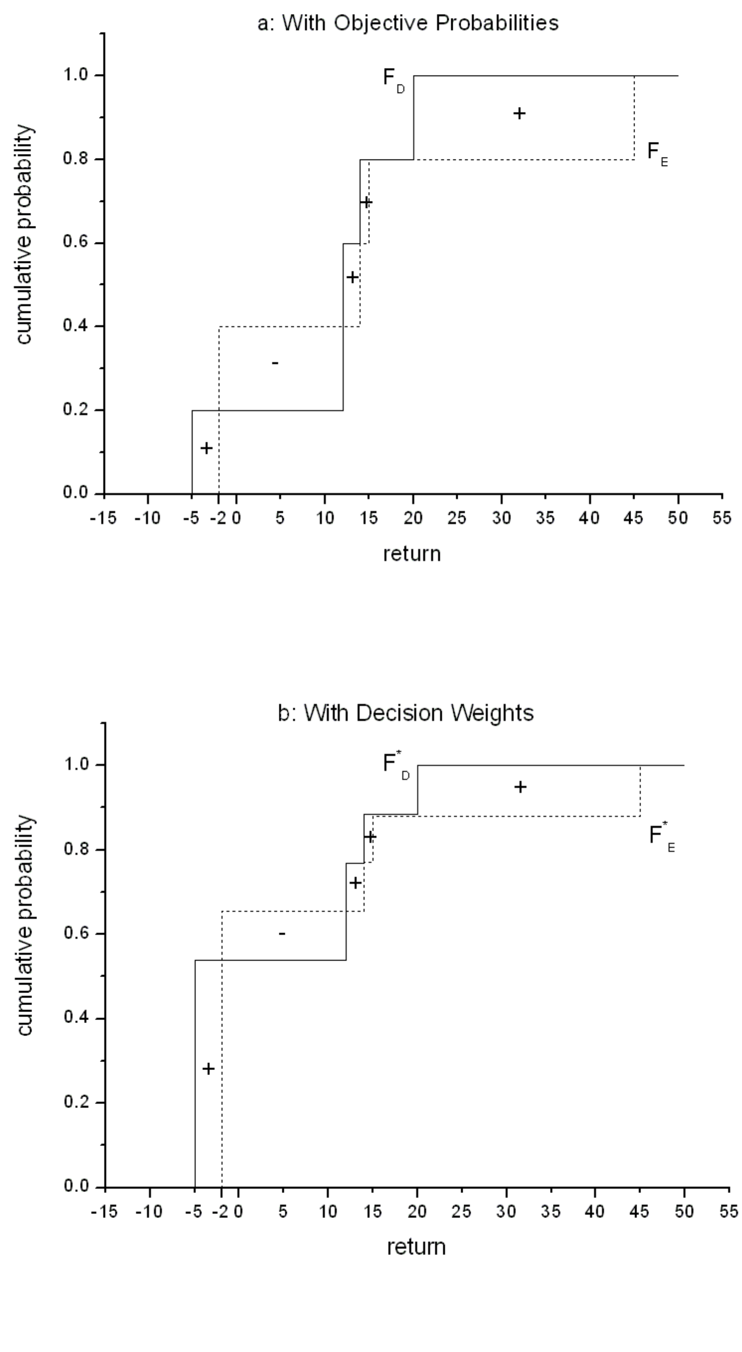
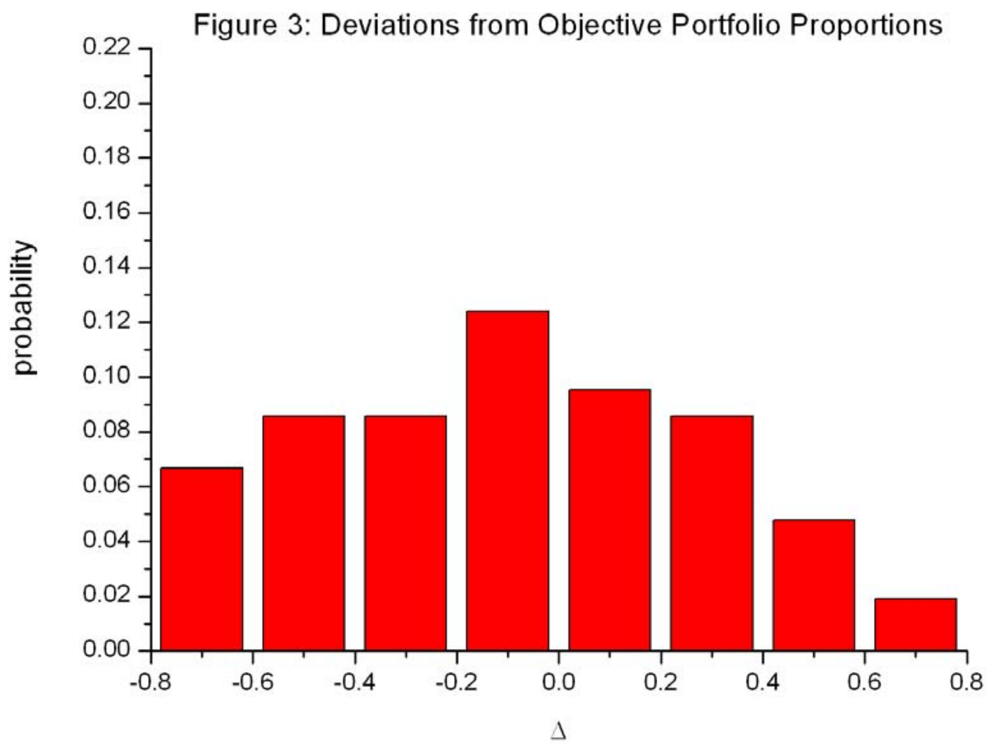


Figure 1: The Funds in Experiment I

# Figure 2: The Cumulative Distributions of D and E






The deviation $\Delta$ is defined as follows: $\Delta_i \equiv \frac{x_i^{dw} - x_i^{ob}}{x_i^{ob}}$, where $x_i^{ob}$ is the proportion of asset i in the optimal portfolio derived with the objective probabilities (1/n), and $x_i^{dw}$ is the proportion of asset i in the optimal portfolio derived with the experimentally found decision weights.

Figure 4: SML with Objective Probabilities and with Decision Weights