When do structured funds become too good to be true? An experiment

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Abstract: Structured funds, with different combinations of secured and additional risky benefits, are sequentially offered to university students who act as investors. In this experiment participants are also offered the alternative choice to buy bonds. Our results show that information available to investors, and particularly the order in which this information is presented, generates significant biases in their decision making. These biases can have both positive and negative consequences on investor's financial behavior. In fact, when the investment alternatives are made easier to compare by showing the funds in increasing order of expected return, too good to be true investment offers get more easily spotted. Whereas simultaneously, when fund's expected performance presents an apparently positive trend (also due to being sequentially shown in increasing order), funds result overvalued in comparison to bonds.

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Jel Codes: G23, C91, G02.

1. INTRODUCTION

Structured products make up a significant part of most developed countries' financial systems. According to the SPA (Structured Products Association) over 180 billion $ were invested in the European fund market in 2005, 70 billion $ in the United States and almost 50 billion $ in the Asian market. In the last years market trends have changed little despite the Great Recession. In 2012, according to the Financial Times, the sales of structured products continued on the rise despite warnings of the financial regulators about their risks and complexity.

Parallel to the growth of structured products in particular, the growth of the mutual funds industry over the recent decades highlights the ability of these funds to channel investors' money into the financial markets. Khorana and Servaes (2012) report that assets in the mutual fund industry increased by a factor of 200 in the period 1976-2009. Moreover, about 45% of the households in the U.S. invest in them, according to ICI (2010). Investment in mutual funds is then a widespread activity which also non-specialized agents undertake. In fact, many citizens invest in guaranteed mutual funds under the form of retirement plans.

The significant role of mutual funds in most markets has aroused both social and academic interest. Within this context, the aim of the present paper is to analyze the individual demand for structured mutual funds according

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to different levels of expected return differential when compared to a bond, and under different information conditions.

The demand for mutual funds has been extensively analyzed in the literature concerned with evaluating fund efficiency. An example of research on structured products demand is Breuer et al. (2007) who successfully explain demand for two of them using a modified hedonic framing rule. Behavioral biases have already been found in experimental studies focusing on mutual funds. Annaert *et al.* (2005) carried out an experiment on framing in capital guaranteed funds and observed that investors tend to choose in a different way when they are aware of some characteristics of the probability distribution of the potential gains/losses. Barreda-Tarrazona *et al.* (2011) experimentally analyzed the importance of providing accurate information about the socially responsible character of a mutual fund in order to help investors express their ethical preferences.

Kliger *et al.* (2003) also opted for an experimental approach to uncover inconsistency with standard Expected Utility Theory in mutual fund investor behavior: investors' tendency to delegate money to a fund increases with performance, even when performance is uninformative. Choi *et al.* (2010) designed an experiment to study the "law of one price" in fund investment. They presented the subjects with a menu of four funds with the same fundamentals but charged higher fees for the funds presenting higher past performances (due to the different launching dates). The authors found that people heavily relied on the annualized past return of funds in making fund selection decisions, even ignoring the fees in many cases. Similar results were obtained by Anufriev *et al.* (2012) in an experiment in mutual fund choice, but in their case, centered on the role of past information and fee structure. They observed that fund choice decision is heavily driven by past return, even when this information is irrelevant. A very similar bias to this one is also obtained in our experiment for the role of information about alternative scenarios.

The above-mentioned literature analyzes investor behavior and demand for mutual funds and in most cases unpredicted behavior appears, to a great extent related to the information available to the investors or to the framing of that information. These articles add to a growing body of evidence that individual investors make suboptimal asset allocation decisions. The present study proposes a simple experimental design, which allows for an analysis of individual investor behavior in structured mutual funds according to variables such as expected return and risk (we vary the former while we keep the latter constant), and, at the same time, tries to eliminate possible behavioral biases such as past performance effect, disclosure of the probability distribution of the potential gains/losses effect, or other features that might difficult comparisons: fees, non-portfolio services, etc. This approach also allows us to evaluate the effect that the structure of the available information has on investor behavior and, consequently, on the demand for the funds.

The study was undertaken in the Laboratory for Experimental Economics (LEE) at the Universitat Jaume I where a sample of university students made investment decisions according to different expected return and information conditions. They had to invest a fixed amount either in a bond or in a structured product, which secured part of the invested capital and yielded additional benefits if the (simulated) stock market experienced a positive evolution. Our results show that information available to investors, and particularly the order in which it is presented, generates significant biases in their decision making that can have both positive and negative effects on their behavior.

The paper is organized as follows: in the next section we outline the design of the experiment. In the third section we present our hypotheses. Then, we analyze the results obtained in the experiment. After that, the main conclusions drawn are presented.[1]

2. THE EXPERIMENT

2.1. Participants

A total of 514 undergraduate students from different majors, mainly business administration, engineering and economics, participated in the between-subjects study: 287 in Treatment 1 and 227 in Treatment 2. Subjects were recruited using the Orsee System (Greiner, 2004) and none of them participated in more than one session. Our experiment consisted of 60 scenarios with the agents having to choose between two investment options in each of them: a risk free asset (a bond) and a structured mutual fund. Each of the 60 scenarios presented a particular combination of the interest rate of the bond on one hand, and the secured and expected additional benefits of the fund, on the other hand.
The experiments were programmed in PHP and Java and carried out in the Laboratory for Experimental Economics (LEE) at Universitat Jaume I in Castellón, Spain. In order to give a real value to each of the decisions made using experimental units (EU), the equivalence of 1 € = 8,000 EU was introduced. Average earnings were 163,962 EU (20.5 €) per participant in about one and a half hour.

2.2. Experimental design and framework

The experiment consists of three parts. The first part is the most central to this research: subjects make investment decisions in each one of 60 scenarios. The second part of the experiment is a risk aversion test using a lottery task. And finally, in the last part of the experiment, subjects fill out a personal questionnaire.

For the first part of the experiment, subjects were given specific instructions about their tasks, which were also read to them aloud by the experimentalist. The experiment was then run for each subject on an individual computer. A screen appeared for each scenario and the investor had to choose where to invest her total endowment of 100,000 EU between two investment alternatives, “A” or “B”.[2]

The investment alternative “A” was a fixed return risk-free bond. Equation [1] describes the final value of the investment after n periods ($V_{n,j}$) for the j scenario as the result of reinvesting the initial V_0 up to n yearly periods, given a simple r_j capitalization. In the experiment setting, for each scenario, n is equal to 3 years and V_0 is 100,000 EU. In Treatment 1, for scenarios going from 1 to 30, this investment yields a 3% annual interest which implies within 3 years a 9% appreciation. In order to simplify to the maximum the investor’s calculations, the

[1] The experimental instructions and the questionnaire are available upon request to the authors.
[2] Note that the investors could not divide their endowment, they had to invest it fully in one of the two options presented to them.

yields were calculated with a simple capitalization. Starting with the scenario number 31 up to the 60th, the bond yields a 7% yearly which implies a 21% r_j in three years (see Table 1).

$$V_{n,j}^{A} = V_0\left(1 + r_j\right) \quad [1]$$

On the other hand, the alternative "B" was to invest in a structured mutual fund. At the end of a three year period this investment fund has a final value as the expression [2] shows. The first component represents a guaranteed part of the investment ($1+g_j$) which varies from -3% to 12% depending on the scenario. Technically speaking, it is when this percentage is positive that we can actually consider the fund a guaranteed mutual fund. The second component yields an extra value depending on the positive evolution of an index representing the stock market. In each of the scenarios, subjects are offered a particular percentage (ρ_j) over the appreciation of the stock market (r_m). As equation [2] shows, this component is asymmetric, given that it yields an additional benefit in case the stock market appreciates, but does not entail losses when the stock indicator does not have a good performance. This asymmetry is typical of the options.[3]

$$V_{n,j}^{B} = V_0\left(1 + g_j\right) + V_0 \cdot \max\left(0, \rho_j \cdot r_m\right) \quad [2]$$

In Treatment 1, every five scenarios the value of the upside participation ρ_j is successively: 10, 30, 60, 100 and 110 percent. This structure is repeated twelve times throughout the whole session. Table 1 summarizes the values of g_j and ρ_j parameters in each scenario for the fund investment "B" as well as r_j for the bond investment "A". Please note that the particular order of the scenarios presented in Table 1 was only used in Treatment 1, while in Treatment 2 the exact same scenarios were presented in different random orders to each of the subjects.

Table 1

Along the 60 scenarios, the table reports the values of the 3-year return (r_j) in [1] for the A investment. For the B investment, we report the values of the 3-year return of the guaranteed part, (g_j) in [2], and the upside participation on the stock market 3-year return of the option part, (ρ_j) in [2].

	Alternative A (Risk-free bond)	Alternative B (Structured mutual fund)			Alternative A (Risk-free bond)	Alternative B (Structured mutual fund)	
Scenario	Guaranteed 3-year return(r_j)	Guaranteed 3-year return (g_j)	Percentage over the (+) stock market 3-year return (ρ_j)	*Scenario*	Guaranteed 3-year return(r_j)	Guaranteed 3-year return (g_j)	Percentage over the (+) stock market 3-year return (ρ_j)
1	9%	-3%	10%	*31*	21%	-3%	10%
2	9%	-3%	30%	*32*	21%	-3%	30%
3	9%	-3%	60%	*33*	21%	-3%	60%
4	9%	-3%	100%	*34*	21%	-3%	100%
5	9%	-3%	110%	*35*	21%	-3%	110%
6	9%	-1.5%	10%	*36*	21%	-1.5%	10%

[3] Actually, the mutual guaranteed funds are products normally structured by means of investment in bonds which at the due date provide the invested capital security, and the payment of an option premium which is bounded to a certain stock market evolution gives us the second component. Holmen et al. (2012) experimentally study how option-like incentives in asset markets can induce higher prices and more risk taking by agents.

7	9%	-1.5%	30%	*37*	21%	-1.5%	30%
8	9%	-1.5%	60%	*38*	21%	-1.5%	60%
9	9%	-1.5%	100%	*39*	21%	-1.5%	100%
10	9%	-1.5%	110%	*40*	21%	-1.5%	110%
11	9%	0%	10%	*41*	21%	0%	10%
12	9%	0%	30%	*42*	21%	0%	30%
13	9%	0%	60%	*43*	21%	0%	60%
14	9%	0%	100%	*44*	21%	0%	100%
15	9%	0%	110%	*45*	21%	0%	110%
16	9%	3%	10%	*46*	21%	6%	10%
17	9%	3%	30%	*47*	21%	6%	30%
18	9%	3%	60%	*48*	21%	6%	60%
19	9%	3%	100%	*49*	21%	6%	100%
20	9%	3%	110%	*50*	21%	6%	110%
21	9%	6%	10%	*51*	21%	8%	10%
22	9%	6%	30%	*52*	21%	8%	30%
23	9%	6%	60%	*53*	21%	8%	60%
24	9%	6%	100%	*54*	21%	8%	100%
25	9%	6%	110%	*55*	21%	8%	110%
26	9%	7.5%	10%	*56*	21%	12%	10%
27	9%	7.5%	30%	*57*	21%	12%	30%
28	9%	7.5%	60%	*58*	21%	12%	60%
29	9%	7.5%	100%	*59*	21%	12%	100%
30	9%	7.5%	110%	*60*	21%	12%	110%

As in real financial markets, the value of the stock market evolution r_m is not known. For this experiment we considered it a random variable with a normal distribution. Even though any simulated data could have been used, we have taken the annualized standard deviation of the Ibex 35 daily return over the three year period 2008-2010 and the annualized mean of the daily return over the past 10 years. As this mean is positive, the probability of a positive r_m is higher than that of a negative value, which is something expected from the equity risk premium hypothesis.

Subjects were informed about investment in stock markets being a risky investment. They were also informed that in the simulated stock market there was a 60% probability for the revaluation to be positive and a 40% probability for it to be negative. And the standard deviation and a table summarizing the distribution of r_m were reported in the instructions. These values were generated, as we explained above, using a normal distribution for the 3-year return with 12.021% mean and 46.8% standard deviation parameters.

After the 60 scenarios were run and all subjects made their choices, the program randomly provided a value for r_m drawn from the aforementioned normal distribution and converted to 0 in case it was negative. Immediately afterwards, one of the subjects volunteered to cast the dice in order to randomly obtain a value *j'* from 1 to 60 which selected the scenario that would be paid out in cash in that session[4]. Finally, subjects who had decided to invest in option A in the selected scenario received the amount corresponding to equation [1] and for those who

[4] In fact, two role-play dice were used, the regular one with six faces (1-6) determined the first digit and the second one with 10 faces (0 to 9) determined the second digit. Note that the 6 in the first dice could mean either 0 when accompanied with any value greater than 0 in the second die, or 6 when the second die showed a 0.

had chosen investment B, their earnings were determined by equation [2] according to the realized value of r_m and the parameters g_j and ρ_j for the selected scenario *j'*.

We ran 9 sessions of Treatment 1 in which the scenarios were sequentially presented as shown in Table 1 (with increasing expected returns for the fund).

In Treatment 2, the exact same 60 scenarios (combinations of fixed and additional potential benefits of the two investment options) were presented in random order, independent for each subject, to a new pool of subjects. We ran 5 sessions of Treatment 2.

Our target was, within each treatment, to observe any changes in the way the capital endowment was invested in the risky or risk free assets in each scenario when the expected return varied, and between the two treatments, to see if the ordering in which the investment scenarios were presented to the participants made a difference in their investment decisions.

In the second part of the experiment, we used a lottery to assess the subjects' risk aversion very similar to the one used by Alfarano *et al.* (2006), which is a modification to a H-L lottery test where one of the options is not probabilistic and increases sequentially in its fixed value and the other is probabilistic but its expected value remains fixed. In this part of the experiment eleven lottery choices are displayed. The risky option, which remains available along the eleven scenarios, is to obtain 48,000 EU or zero EU with 50% probability. The safe option consists of a secure payment which ranges from 4,000 UE in the first scenario, to 31,000 UE in the last one. After all choices are made, one of the eleven scenarios is randomly chosen[5] and also the 50% probability situation is solved by a volunteer tossing a coin. Then the payment to each participant in the risk lottery is determined according to these events. An expected rational behavior would be to choose the risky option in the first scenarios when the riskless offer is low and afterwards, with higher secured yields, switch to the safe option at some point of the decisions chain.[6]

Finally, the third part of the experiment consisted of a questionnaire with demographic and idiosyncratic data. The first three questions were meant to reveal the financial knowledge level of the participant. The following four questions evaluated how important investment yields and risks were for the subject and whether they had any asymmetric perception in the evaluation of gains and losses. The last four questions aimed at evaluating subject's rationality when selecting investments.[7]

3. HYPOTHESES

In the mean-variance framework for choosing among financial assets, for a given level of risk, an asset offering a higher expected return would always be preferred over one with a lower expected performance. In our design, the only risk faced by the participants concerns the future evolution of the computer simulated stock market r_m, on which the variable part of the structured fund return is based. In this way the underlying risk is kept constant

[5] This was done by a volunteer subject throwing a 12-sided die, where if 12 turned out she had to cast the die again.
[6] The analysis of the data obtained from the risk aversion test is available upon request from the authors.
[7] The data obtained from the questionnaire did not result significant in the econometric analysis.

for all the guaranteed products. On the other hand, the alternative investment possibility is a risk-free bond. In this setting, the binary decision of choosing between the two investments should be made in terms of the subjectively calculated expected utility of each alternative according to each individual's level of risk aversion. When one of the investment alternatives unequivocally increases its expected return with respect to the other without varying its risk, it should be more preferred by our investors. This can be expressed as appears in our Hypothesis 1:

H.1 Investment in the structured fund is increasing in the difference between the expected return of the structured fund and that of the risk free bond.

We stated that the expected utility is subjectively calculated by each investor. This is due to the fact that not every person is risk-neutral. In fact in the experimental literature there is ample evidence that people tend to be risk-averse even for the relatively small amounts of money they can gain in experiments. As the only risk in our experimental design concerns the structured fund, this will be in general the least preferred option for the more risk-averse investors, and vice-versa:

H.2 Risk-averse (loving) participants will prefer to invest in the bond (structured fund).

We think that this effect could be as important so as to totally nullify the effect of big expected return differentials between the investment options, but only for the extremely risk-averse or extremely risk-loving individuals. We introduce expected return differences up to 30% in the design, which are very big for regular investment standards. Besides, we do not expect many subjects to show an extreme degree of risk aversion or lovingness. Under these circumstances, the aggregate effect of these few subjects' decisions will anyway be very small.

H.3 Extremely risk averse participants will not invest in the structured fund even for highly positive expected return differentials.

According to Miller (1956) "Everybody knows that there is a finite span of immediate memory and that for a lot of different kinds of test materials this span is about seven items in length… and there is a span of absolute judgment that can distinguish about 7 categories." That is, the ability of people to keep in mind and compare a large set of options is limited. In our case we presented each subject with 60 binary choices. In Treatment 1 the information was presented sequentially, in cycles with increasing order of expected returns, so that it was easy for the subjects to categorize and compare the different assets across the scenarios. According to the psychological research on the matter, in Treatment 1, subjects should be able to recall and easily compare at least within each group of 5 scenarios with stable fixed returns for both investments and increasing index-performance related expected returns. However, in Treatment 2, the sequence of scenarios did not follow any logic and what was "stored in memory" was a juxtaposition of a steadily increasing number of offers with different expected values.

Malhotra (1982) found that respondents experienced information overload when they were presented with 10, 15, 20 or 25 choice alternatives. If the independence of irrelevant alternatives held in our case this would not pose any problem, because all 60 binary choices are independent in our design, in the sense that only one of the scenarios was to be selected in the end, and all other 59 choices would be totally irrelevant for determining the payment to the particular subject. No matter how attractive or unattractive an investment seen in prior scenarios was, that should not have any weight in the binary decision being presented in a particular alternative scenario. However, if the subject tried to keep in mind all the investment options that were presented to her in order to carry out a global comparison, she would soon be confronted to her memory and judgment limits.

H.4 The order in which information is presented to our participants (sequential vs. random) will generate biases in their decisions related to information processing limitations: i) a sequential presentation of better alternatives can introduce return chasing, as has been previously observed in the literature, but, on the other hand, and thanks to our design, ii) it can make the extremely generous offers seem too good to be true.

Our argument is that the memory and judgment limitations, operating when the investment options are presented randomly, are greatly reduced when these are sequentially ordered in groups of five choices in which the only difference is the increase in the upside market participation. This increase may make the guaranteed option become more attractive in comparison to the bond than what the difference in expected returns would justify. However, when the upside market participation (which increases from 10% up to 110%) goes above 100% it could appear to be “too good to be true”, i.e. the guaranteed investment may seem to be offering too much. In this case, subjects could come to doubt the likelihood of a positive stock market return stated in the instructions.[8]

4. RESULTS

4.1 Aggregate results on guaranteed mutual funds investment.

Figure 1 offers us some graphical evidence of hypotheses 1 and 2. It allows us to infer from the subject’s choices that a very reduced number of people are highly risk loving or highly risk averse and they stick to their preferred option: the risky or the safe one respectively, both in the presence of highly positive or highly negative return differentials between the fund and the bond. In fact there are probably more extremely risk averse subjects than extremely risk lovers (around 9% and 1% respectively). However, most investors (approximately 90%) change their decision in the hypothesized way alongside the evolution of the expected return differential between the two assets following a sigmoid logistic shape.

[8] In fact, for a high guarantee, a real firm which could sell this particular fund would lose money in case of a positive revalorization of the stock exchange.

Figure 1

Percentage of investors choosing the structured fund according to its expected return difference with the bond.

Comparing the two treatments visible in Figure 1 we can observe that in Treatment 1, when the scenarios are easier to compare (because they were presented in the sequential order shown in Table 1), the percentage of people investing in the guaranteed fund is greater for most expected return differentials (full dots are normally placed higher than hollow dots). So, investors have a higher preference for the fund when they can easily compare the independent scenarios and observe that the fund offers increasingly higher expected gains, while the bonds' remain constant. This is the first casual evidence of our Hypothesis 4.i.

This observation supports the idea that investors may suffer from a kind of "past returns" or "trend" illusion, similar to Chartism, due to which they tend to believe that a good history is in some way guarantee of a good future performance, even in totally independent realizations as those presented in our experiment. This result is complementary to the ones recently obtained by Choi *et al.* (2010) and Anufriev *et al.* (2012), even though our situation is not identical, given that the offers that we present to the investors correspond to alternative worlds that might be realized in the end or not, and not to real past performances.

This "trend" effect can also be observed numerically in Table 2a. In order to statistically support our graphical observations above, we have conducted a battery of Kolmogorov-Smirnov tests between the distributions of subject's proportions of structured fund choice for different groups of scenarios and we have obtained statistically significant evidence that T1 distribution stochastically dominates T2's for the whole sample and for the two 30 scenarios subsamples.[9]

[9] Only when we further break down the sample into the 12 cycles of 5 periods we obtain that the difference is significant in half of the cycles, very precisely matching what appears in Figure 2.

Table 2a
Proportion of investors that chose the structured fund for different groups of scenarios.

	All	Half	(I)	(II)	(III)	(IV)	(V)	(VI)
Scenarios:	1-60	1-30	1-5	6-10	11-15	16-20	21-25	26-30
T1 Average	52.39%	64.64%	52.12%	54.14%	62.22%	67.03%	73.93%	78.39%
T2 Average	47.23%	58.82%	40.70%	39.20%	60.96%	62.20%	72.07%	77.79%
Kolmogorov-Smirnov p-value	**0.000**	**0.000**	**0.000**	**0.000**	0.846	0.155	0.315	0.400
Scenarios:		31-60	31-35	36-40	41-45	46-50	51-55	56-60
T1 Average		40.13%	21.95%	28.15%	38.67%	42.43%	48.98%	60.62%
T2 Average		35.65%	20.17%	21.76%	34.44%	35.59%	43.70%	58.23%
Kolmogorov-Smirnov p-value		**0.003**	0.632	**0.060**	0.449	**0.020**	**0.028**	0.542

Table 2b
Median number of scenarios in which agents chose the structured fund and Mann-Whitney test between treatments

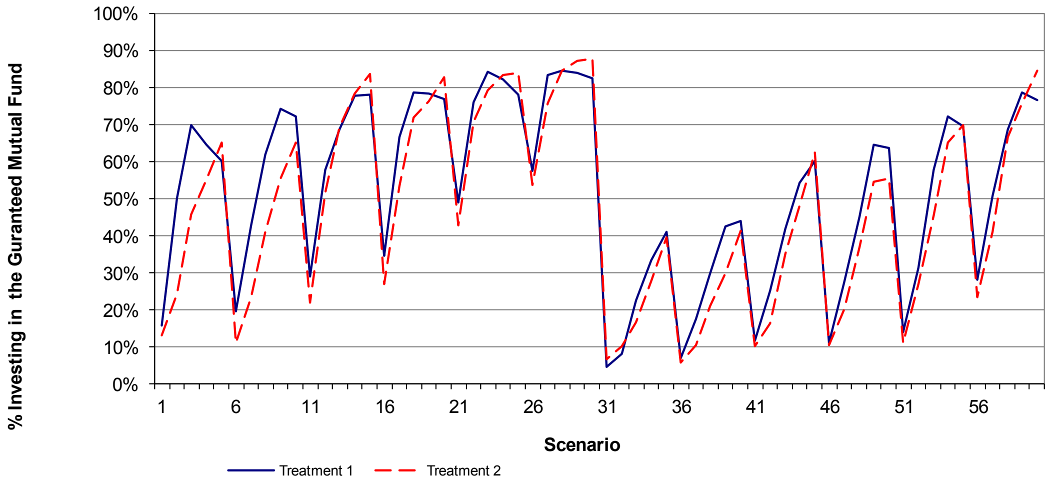
Scenarios:	All	Half	(I)	(II)	(III)	(IV)	(V)	(VI)
	1-60	**1-30**	1-5	6-10	11-15	16-20	21-25	26-30
T1 Median (287 obs)	33	20	3	3	3	4	4	4
T2 Median (227 obs)	28	18	2	2	3	3	4	4
Mann-Whitney p-value	**0.0002**	**0.0001**	**0.0000**	**0.0000**	0.4801	**0.0207**	0.1591	0.2811
	Scenarios:	**31-60**	31-35	36-40	41-45	46-50	51-55	56-60
T1 Median (287 obs)		12	1	1	2	2	3	3
T2 Median (227 obs)		10	1	1	2	2	2	3
Mann-Whitney p-value		**0.0231**	0.7286	**0.0209**	0.0944	**0.0021**	**0.0134**	0.2815

In Table 2b we compare the median number of scenarios in which subjects invested in the structured fund (instead of the whole distribution of the proportions of investors), obtaining robust results supporting the statistical significance of a positive difference in median investment in the guaranteed fund in T1. The median number of scenarios in which subjects selected the guaranteed fund is 33 out of 60 in T1, while only in 28 out of 60 in T2. In fact, performing an additional Mann-Whitney test we obtain that the probability for a random scenario that a randomly chosen agent from T1 has selected the guaranteed fund more often than a randomly chosen agent from T2 is 60%. *The tests above offer evidence consistent with our Hypothesis 4.i, confirming the existence of a "trend" effect.*

If we analyze Figure 2, which describes the evolution along the scenarios of the percentage of investment in the structured fund, behavioral paths can be identified.

Figure 2

Guaranteed mutual fund investment along the 60 scenarios of the experiment for T1 and T2



The guaranteed return of the mutual fund offers -3% in the first group of 5 periods, while the bond ensures a 9% return on the investment for the same time horizon. In the first period, with an additional 10% yield over the stock market revaluation for the mutual fund, only 18% of the participants prefer the risky option, which seems to indicate that a maximum 12% loss is compensated for them by a highly positive expectation on the evolution of the stock market. In Treatment 1, within this first group of five scenarios there is a maximum investment in the Fund option in the third scenario where a 78.9% of participants decide that a 12% maximum loss from investing in the mutual fund instead of the bond is compensated by a 60% upside participation. In the subsequent 4th and 5th scenario we observe a fall in the mutual fund investment: 77.5% and 71.8% of investors decide to invest in the fund for a ρ_j value of 100% and 110% respectively. This pattern is not infrequent in Treatment 1: in the second group of five scenarios a similar phenomenon is also observed, that is, mutual fund investment rises from 21.1% in the first scenario up to 85% in the 4th scenario where it reaches the maximum and finally in the fifth scenario of the second group of 5, when the ρ_j value goes beyond 100%, investment in the fund drops to 79%. This extreme concavity feature is repeated along the whole Treatment 1, especially in the scenarios 1 to 30 where the difference between the guaranteed three years return of the bond and the guaranteed part of the mutual fund is narrower than it is for the last 30.

This is in our opinion the most original result of this experiment. While one would expect a monotonic increase in investment in each 5 scenarios cycle together with the increase in the upside participation, we observe that for percentages higher than 100% investment in the structured product in fact nearly always decreases in Treatment 1. We call this finding the “too good to be true effect”, which has some implications for the advertisement of structured products. Offering such high upside participations could in effect be conveying to the risk averse investor the idea that the event of the stock market actually revaluating is highly unlikely, because otherwise such great upside participation would not be offered. In our experimental case, students may doubt whether in the scenarios where the offer is so high the actual probability of a positive revaluation really is 60% as stated in the instructions.

However still in Figure 2, we can also observe that the “too good to be true” effect totally disappears as soon as the subjects are no longer able to easily compare all the possible investments. Just more of them invest in the fund when the upside participation is 110% than 100%. Seeing all the binary options in random order seems not to make them behave more cautiously for extremely high offers.

In order to provide statistical evidence for the “too good to be true” effect we have conducted a McNemar symmetry test. This test compares whether the number of times that an agent was choosing the guaranteed fund when ρ_j was 100% and he decided to switch his selection to the bond when ρ_j increased to 110% is significantly different from the opposite switch, that is, that an agent was choosing the bond when ρ_j was 100% and decided to change to the fund for 110%. Our results can be found in Table 3. For the first 30 scenarios of treatment 1 we find that significantly more times the case was that those choosing the fund switched to the bond, thus statistically supporting the “too good to be true” effect. For the last 30 scenarios of T1 there is no significant decrease in fund investment, but also no significant increase -still consistent with our hypothesized effect-, while for both the 30 first and the 30 last scenarios of T2 we observe the opposite phenomenon: that significantly more people switched from the bond to the fund when the upside market participation increased over 100%, as expected if no “too good to be true” effect applies and investors just follow the guide of the expected return difference. *These tests together support our Hypothesis 4.ii that a “too good to be true” effect arises when the relatively better and worse investment scenarios are made easier to compare.*

Table 3
Number of observations choosing the fund for a 100% upside participation switching to the bond for 110% *versus* number of observations choosing the bond for 100% upside participation switching to the fund for 110%

Scenarios:	1st Half	2nd Half
	1-30	**31-60**
T1 (1722 obs)	142 vs. 105	110 vs. 138
McNemar p-value	**(-) 0.0218**	(=) 0.0862
T2 (1362 obs)	121 vs. 196	138 vs. 257
McNemar p-value	**(+) 0.0000**	**(+) 0.0000**

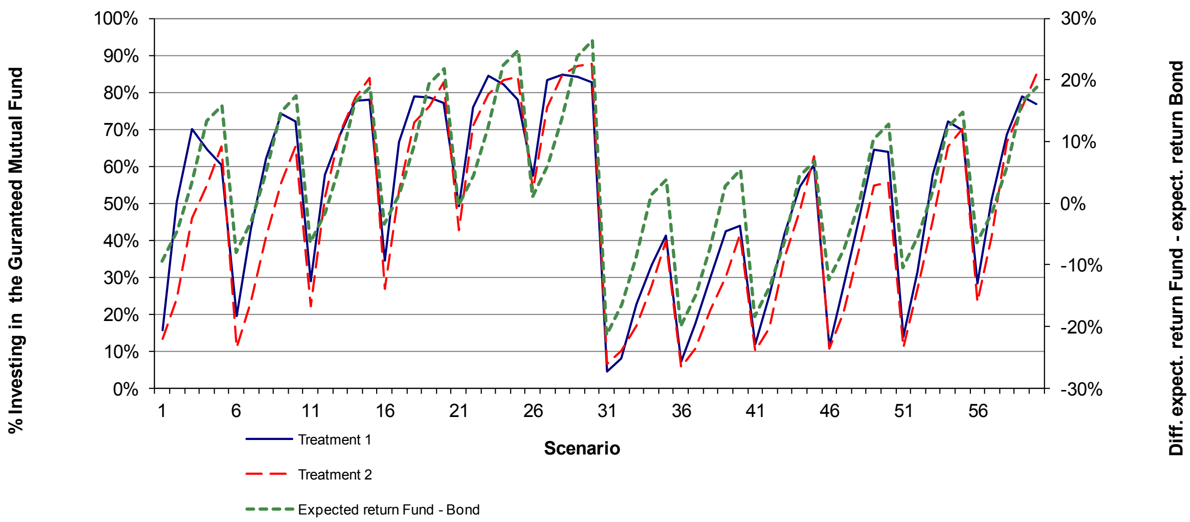
+/- Stands for an increase/decrease in the relative fund purchases when the upside market participation increases from 100% to 110%

That is, in T2, when subjects see the 100% and 110% upside participations in random order mixed with the other lower ones (without observing the sequential increase in each 5 scenario group) they do not infer any negative signal in such attractive offers. Thus, spotting “nearly incredible” offers becomes harder when comparing offers becomes cognitively harder. This fact has implications for financial regulatory authorities. Clearly organizing and categorizing existing investment opportunities could help investors in discriminating reasonable offers from highly unlikely to be fulfilled ones. We still do not know how many times yet a Ponzi scheme will be successful in alluring naïve investors.

Figure 3 shows the expected return differences between the fund and the bond for each scenario. In this way they can be used as a benchmark for rational risk neutral decision makers. As our participants varied in their degree of risk-aversion we never observe that all investors follow the clear-cut risk neutral prediction. However, we do observe that the percentage of investors choosing the fund approximately follows the difference between the expected return of the fund and the bond, as proposed by Hypothesis 1. This link is clearly broken only for Treatment 1, in the scenarios where we observe the "too good to be true effect".

Figure 3

Difference in expected returns between the guaranteed fund and the bond for each scenario against the evolution of the percentage of investors choosing the fund in the two treatments



4.2 Econometric analysis.

In this section we further analyze the statistical significance of our results using panel regression methodology. In order to obtain a more precise measure of the impact of the guarantee and the stock market upside participation on the demand for the mutual fund investment we construct a model using as independent variables those appearing in equations [1] and [2]: the guaranteed return of the bond (r_j), the guaranteed return of the structured fund (g_j), and the upside participation offered by the fund (ρ_j). We have also introduced in the analysis the individual level of risk aversion estimated from our lottery tests (the higher the value the less risk aversion a subject showed in the test). Besides, we also employ as a variable the squared term of the upside participation ($\rho_j^{\,2}$) with the aim of capturing, when this quadratic effect is significant, the concavity of the demand of the mutual fund. This concavity must be big for the "too good to be true" effect to be significant.

The obtained data form a panel with 514 individual decisions across 60 periods (287 in Treatment 1 and 227 in Treatment 2). Given that we identified around 10% investors with non robust answers to the risk aversion test, the respective observations were eliminated from our analysis and we remained with a still relatively large sample of 467 robust individuals (262 for T1 and 205 for T2) and a total of 28,020 usable observations for our panel data analysis.

Table 4 (Panel A) contains the main results that we obtain by running a probit model for Treatment 1 in the first column, for Treatment 2 in the second column, and finally for the difference between the parameters estimated for the two treatments in the third column. Starting with Treatment 1, all variables turn out to be highly significant and they all have the expected sign. For example, an increase of the return (r_j) of option A (the bond) has a negative effect on the mutual fund demand, while a higher guaranteed value (g_j) of option B (the fund) increases its demand. Also positively, but in a lower proportion, the upside participation (ρ_j) increases the mutual fund demand. *All these three significant results together statistically confirm our Hypothesis 1.* The negative coefficient of the squared term of the aforementioned upside participation confirms our preliminary graphical analysis, which indicated a concave shape of the demand for the mutual fund as a function of the upside participation. The effects concerning ρ_j and ρ_j^2 deserve a more detailed analysis that we will undergo when we consider the difference between both treatments (third column).

We also find that in a scale from 1 to 12 of risk attitude (1 is very risk averse and 12 is highly risk lover), one additional level in this scale, that is, being characterized as more risk lover, entails a significantly higher probability to choose the structured fund. *This confirms our Hypothesis 2 that those subjects relatively less risk-averse invest with higher probability in the risky option.*

When we turn to treatment 2 (second column) we observe that all the mentioned significant effects are robust, but they are smaller, with the exception of the effect of the guaranteed return of the fund. But, are these differences in the size of the coefficients significant? In the third column we check for the significance of the differences between the coefficients estimated for the two treatments and we obtain that those for the bond returns, risk aversion and also the intercept are not significantly different between treatments. The positive effect of the guaranteed return of the fund is slightly greater in T2. This is true particularly in the first 30 scenarios when the bond return is relatively low, as we can observe in Panels 4B and 4C. In those panels we separate the sample into the observations of the first 30 and the last 30 scenarios (when ordered as in Table 1).

And the most important differences between the two treatments (third column of Panel 4A) are, firstly, that the positive effect of the upside participation on fund demand is significantly reduced to two thirds in Treatment 2 when the investment options are made harder to compare, thus econometrically confirming the "trend" effect, and secondly, that the concavity of the demand function with respect to this upside participation is also significantly halved for T2, dramatically reducing the "too good to be true" effect (these results are robust for all scenarios as we can observe in panels 4B and 4C). *These two observations together further confirm our Hypothesis 4.*