Experiments on heterogeneous expectations and switching behavior

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Chapter 5

A Simple Experiment on Fee Structure and Mutual Fund Choice

5.1 Introduction

Mutual fund selection is a very important investment decision for many families in industrialized countries, as well as a very important topic for studies on the stability of the financial market. According to Investment Company Institute (2012), total world asset invested in mutual fund is 23.8 trillion, which is more than one third of the world GDP. 44% of US households own mutual funds, and the median of mutual fund assets owned per household is 120,000 US dollar. The Many studies on mutual fund selection focus on the following two basic questions:

1. Do people make an optimal choice between funds?

2. What are the main factors that drive people’s choice decision?

Two recent studies provide insightful answers to the questions. In Choi et al (2010), the authors find that people heavily rely on the annualized past return of funds in making fund selection decisions. They design a field experiment where the subjects choose between four
funds that are based on the same index, and therefore have exactly the same fundamentals, and will generate the same returns. In the manuals of the funds, however, they have different annualized past return rate record due to different launching time, and the funds with a high past return record charge higher fees. Although the “law of one price" theorem suggests people should ignore the past return information and simply pick the fund with lowest fee, many of them fail to do so. In an earlier paper by Choi et al (2009), the authors find that people tend to use reinforcement learning in making fund choice decisions. Investors who experience rewarding outcomes from 401(k) saving tend to increase their savings level more than they should.

Another study by Barber et al (2005) find that fee structure matters a lot for mutual fund selection. Two types of fee structures are commonly used in practice. One is called front end load, which is a fixed commission charged by the fund when the investor purchases the shares of the fund. The other type is called operation expense or operation fee, which is a management fee paid to the fund usually charged during the period the investor invests in the fund. The fee rate of a front end load is typically larger than operation expense. Therefore front end load is usually considered more salient than operation expense. The authors find that money inflow to mutual funds is negative correlated to front end load fee, but not correlated to operation fee. They argue that people pay more attention to the front end load fee than operation fee because the former is more salient and transparent to them.

The main message from these two works to the two questions above is (1) people do not seem to make the optimal choice of funds, and (2) people are affected by information on past return and the way fees are presented to them.

We want to set up an experiment where participants have to choose between two different mutual funds, and where the fee structure differs between funds and treatments. Our main research questions are:

- Investigate the impact the fee structure has on mutual fund choices. Instead of
studying the marginal effect of changing the fee rate on fund choice, we are interested in whether it makes a difference if the same amount of fee is charged in different forms. In particular, does a fee discourage investment more if it is charged in the form of front end load fee instead of operation fee?

- Investigate when participants *switch* between mutual funds, and what the main determinants for this switching are. In particular,

  - are past returns more important in determining choices than fees (this would support Choi et al. 2010)?
  
  - is reinforcement learning a good description of individual investment choices (this would support Choi et al., 2009)?

The advantages of the experimental method for studying these questions are: (1) for studying the fee structure, it is easier to make the total cost from front end load fee and operation fee the same, so the results are directly comparable; (2) for studying how people use past information and learn from past experience, it is easier to make repeated decision in multi-period experiments (in Choi et al, 2010 people only make the choice decision once).

We design an experiment where subjects choose between two experimental funds (A and B). The subjects have information about the data generating process of the returns of the funds, and are aware that the net (after deducting fees) expected return from B is always larger than A. A charges no fee and B may charge no fee, a front end load or an operation fee depending on the treatment. We find that they still do not always choose B. Their choice is affected by past (realized) returns of the funds.

For the effect of different fee structures, we find that subjects choose fund B more frequently and switch less frequently when B charges a front end load fee, than a operation fee. We suppose this may be caused by a “lock in" effect: once a participant invested in the fund that charges a front end load fee, although it is a sunk cost for future decisions,
he or she may still be reluctant to switch to other options. That relates our paper to the
eperimental study on sunk cost by Friedman et al (2007). Subjects in their experiment
decides whether to keep digging “treasures" on an experimental island, or take some cost
to move to another island. They find that subjects tend to stay on islands that were more
costly to find longer. Lock in effect is also related to studies on status quo bias, such as
Brown and Kagel (2009), where subjects show tendency to ignore information on stock
performance and continue holding the stocks they current have.

As an experiment with exogenously generated prices and returns, our work is related
to Bloomfield and Hales (2002), who ask subjects to predict the next step of an earnings
time series that follows a random walk. They find the subjects do not take the random
walk as random, but divide the time series into “trend" and “mean reverting" regimes,
and try to use the frequency of past earnings reversals to predict the likelihood of a future
earnings reversal. Instead of asking the subjects to make predictions, we ask subjects to
make investment decisions. Our work is also related to several empirical and experimental
works that estimate the discrete choice model similar to Brock and Hommes (1997, 1998)
fund choice data to estimate the intensity of choice parameter in the discrete choice model
using US stock market data where agents switch between fundamental and trend following
prediction strategy. Anufriev and Hommes (2012a, 2012b), Anufriev et al (2012) and Bao
et al (2012) calibrate a model using data from learning to forecast experiments where
agents choose from a menu of prediction strategies, and strategies that are successful in
the past attract more followers in future periods. One important purpose of these studies
is to estimate the intensity of choice parameter.

The interest of our experiment relies also on the fact it relates to a more general
literature on the role of prices as signals of quality and on the lack of salience of funds
fees. On the first side, Bagwell and Riordan (1991) for instance show that high prices
generally signal high quality. On the other side, Gabaix and Laibson (2003) and Gabaix and Laibson (2006) show that pricing complexity can exacerbate the salience problem and the concreteness principle pointed out by Slovic (1972). Our experiment allows verifying if investors do relate high prices with high expected returns and therefore investment decisions, and also if they perceive front-end loads as more salient than operating expenses.

The rest of paper is organized as the following: section 2 describes the experimental design, section 3 shows the result, and section 4 concludes.

5.2 Experimental Design

5.2.1 Summary Information

The experiment was run on December 8-9, 2011 in Burgundy School of Business, Dijon, France. The subjects are students of Burgundy School of Business. 76 subjects are recruited (22 in treatment N, 19 in treatment O, and 35 in treatment F). The participants in these sessions were first year master students, who had no experience in participating experiments on similar topics. They all had 2 years training in economics, statistics and math before passing the exam to enter the school, and they took many other business classes after they entered the school. Normally they are reputed to be quite good students because the business school has the right to select 150 students ranked between grades 14/20 and 17/20 at the entrance exam where the total population is of 4000 students (those with grades higher than 17/20 go to HEC in Paris). They could choose to have the instructions in English or French. The duration of the typical session is one and a half hours.

5.2.2 Task Design

The tasks of the participants in the experiment is the following. Each participant is given some starting wealth, $M_0 = 1000$ points, which will be growing during the experiment.
Each period $t = 0, \ldots, T - 1$ the participant has to decide whether to invest its money, $M_t$, in fund $A$, fund $B$, or not at all. The next period money, $M_{t+1}$, depend on the individual decision and an exogenously determined (stochastic) return of the chosen fund. In each session, we run the 3 blocks of 15 periods. We reset the starting capital at the beginning of each block. At the end of the experiment, the subjects are paid according to their final wealth in one of the three blocks with equal probability. An example experimental instruction for this experiment can be found in Appendix A. Before the subjects start the experiment, we ask them to answer several control questions on paper to make sure that they understand the experiment. We start the experiment only when all subjects have answered all control questions correctly. The control questions and answers can be found in Appendix B.

5.2.3 The Mutual Funds: Returns

There are two mutual funds, $A$ and $B$, with given prices, that follow a stochastic process that is common knowledge for the participants. The prices $P_{A,t}$ and $P_{B,t}$ are given as:

$$P_{A,t} = (1 + a + \mu_t) P_{A,t-1} \quad \text{and} \quad P_{B,t} = (1 + b + \eta_t) P_{B,t-1}.$$

Here $\mu_t$ and $\eta_t$ are two independent white noise processes, that can only take on two values $\varepsilon > 0$ or $-\varepsilon < 0$, both with equal probability. Moreover, $b > a > \varepsilon$. The first inequality implies that in expectations fund $B$ generates higher return rate than $A$, while the second inequality implies that independent on realizations of $\mu_t$ and $\eta_t$, both price processes are monotonically increasing.

---

The experimenter throws a dice for each of the subject, the subjects is paid according to his/her final wealth in the first block if the dice shows 1 or 2, the second block for 3 and 4, and the third block for 5 and 6.
For this structure the returns are given by

\[
R_t^A = \frac{P_{A,t}}{P_{A,t-1}} = 1 + a + \mu_t = \begin{cases} 
1 + a + \varepsilon & \text{with probability } \frac{1}{2} \\
1 + a - \varepsilon & \text{with probability } \frac{1}{2}, 
\end{cases} 
\]

\[ (5.1) \]

\[
R_t^B = \frac{P_{B,t}}{P_{B,t-1}} = 1 + b + \eta_t = \begin{cases} 
1 + b + \varepsilon & \text{with probability } \frac{1}{2} \\
1 + b - \varepsilon & \text{with probability } \frac{1}{2}, 
\end{cases} 
\]

\[ (5.2) \]

with expected one-period returns given by

\[
E_1[R_t^A] = 1 + a \quad \text{and} \quad E_1[R_t^B] = 1 + b. 
\]

Note that \( \tau \)-periods expected return of investing in fund \( A \) is given by

\[
E_\tau[R_t^A] = \sum_{t=0}^{\tau} \left( \begin{array}{c} \tau \\ t \end{array} \right) \left( \frac{1}{2} \right)^{\tau} (1 + a + \varepsilon)^t (1 + a - \varepsilon)^{\tau-t} = (1 + a)^\tau
\]

and in a similar way we know the \( \tau \)-periods expected return of investing in fund \( B \) is \( (1 + b)^\tau \).

We design the return time series such that the ex ante expected return of fund \( B \) is larger than \( A \), but the ex post realized return of \( A \) is larger than \( B \) if fund \( A \) incurs a positive realization of the shock and fund \( B \) incurs a negative realization of the shock. If subjects act rationally, they should ignore the information on past realized returns, and simply always choose fund \( B \) since it gives a higher expected return. If agents still choose \( A \) sometimes, especially after \( A \) generates higher realized return than \( B \), this shows that agents rely on information about past returns heavily even when such information is not relevant.
5.2.4 Treatments Based on the Fee Structure

We consider three treatments according to the fee structure used for the experimental funds.

1. **Baseline treatment (Treatment N):** None of the two funds require fees. We set $a_N = 0.03, b_N = 0.04$. Therefore the expected return is 3% for fund $A$, and 4% for fund $B$. In this case the optimal decision is to always invest in $B$.

2. **Operating expenses treatment (Treatment O):** There are operating expenses for fund $B$ only: a fraction $\gamma = 0.01$ of the wealth is paid as a management fee in each period. For simplicity, we assume return and fee occur at exactly the same time. This means that return for $B$ is going to be $R^B_t = 1 + b_O - \gamma + \mu_t$, whereas for $A$ it is the same as it is in Treatment N. We set $a_O = 0.03, b_O = 0.05$. Therefore the expected gross return is 3% for fund $A$ and 5% for fund $B$ (expected net return is 4% for $B$), which implies that the optimal choice should be still to always invest in $B$.

3. **Front-end load treatment (Treatment F):** There is a front-end load fee only for fund $B$, that is, at the moment $t$ when a participant first time decides to invest in $B$ it has to pay a fixed percentage $F$ of his/her investment (i.e., under current design, current wealth $M_t$). The remainder $(1 - F) M_t$ is invested in the fund. After that, if the participant stays in fund $B$, he does not need to pay more fees. But if he or she alternates from the fund and enters again, he or she will be charged the fee again in the first period he enters. Note that at moment $t$, it is optimal to start investing in $B$ (instead of $A$) for the rest of the periods whenever

\[(1 - F) E_{T-t}[R_B] > E_{T-t}[R_A],\]
which can be rearranged as

\[ F < 1 - \frac{E_{T-t}[R_B]}{E_{T-t}[R_A]} = 1 - \frac{(1 + a_F)^{T-t}}{(1 + b_F)^{T-t}} \tag{5.3} \]

In particular, if

\[ F < 1 - \frac{(1 + a)^T}{(1 + b)^T}, \]

then a rational agent should invest in \( B \) from the very beginning. Given an initial mistake to choose \( A \), a decision to switch to \( B \) depends on \( F \) and the number of remaining periods: if at time \( t \) (5.3) holds, it makes sense to switch to \( B \). We set \( a_F = 0.03, b_F = 0.05 \). Therefore the gross expected return is still 3\% for fund \( A \) and 5\% for fund \( B \). The remaining task is to solve for \( F \) which is such that a participant gets exactly the same payoff by always choosing \( B \) in this treatment as he or she gets in Treatment N and Treatment O, which also implies a participant pays the same total amount of fees in this treatment and Treatment O in the rational benchmark. \( F \) will be solved by the following equation:

\[ (1 - F) (1 + b_F)^T = (1 + b_N)^T \iff F = 1 - \frac{(1 + b_N)^T}{(1 + b_F)^T} \]

which gives us

\[ F^* = 1 - \frac{(1 + 0.04)^{15}}{(1 + 0.05)^{15}} = 0.1337 \approx 13\%. \]

We use the same realization of the shock \( \mu_t \) and \( \eta_t \) in all treatments. Therefore any difference we then observe between treatments is then due to the fee structure. In all of these treatments, the optimal decision is, of course, to invest in \( B \).

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\[ \text{In treatment O and treatment F, we make the fund with higher expected return the one that charges a fee just because the choice will be trivial if the fund with lower expected return charges a fee. We are aware that some empirical works show that the fee charged by funds are not necessarily justified by higher returns.} \]
(a) **Block 1:** Prices and returns in treatments N (left) and O and F (right).

(b) **Block 2:** Prices and returns in treatments N (left) and O and F (right).

(c) **Block 3:** Prices and returns in treatments N (left) and O and F (right).

Figure 5.1: Prices and returns for fund $A$ are shown by squares. Prices and returns for fund $B$ are shown by circles. The expected return for fund $A$ is 3% in all treatments, and the expected net return for fund $B$ when a participant always chooses $B$ is 4%.

Figure 5.2 shows a typical experimental screen. Each participant has full information about the price generating mechanisms. They will be shown a table and a graph with the time series of prices ($P_{A,t}$ and $P_{B,t}$). They are also shown the value of their portfolio in each period.

In each treatment participants get three blocks of time series (for example $3 \times 15$ periods in total). We use the same parameters ($a$, $b$ and $\gamma$) for these different sets. The only difference will be that we will use different seeds of white noise.
5.2 Figure 5.2: A typical experimental screen. The subjects make a choice between investing in fund \emph{A}, \emph{B} or neither of them in the upper part of the page. They can refer to the past prices of the funds in the graph in lower left part, and the table in the lower right part. The prices of fund \emph{A} are shown by squares, and the prices of fund \emph{B} are shown by diamonds.

5.3 Experimental Result

5.3.1 Summary Statistics

The first finding from the experiment is that although the data generating process is clear and the theoretical prediction of rational behavior is unique (choosing \emph{B}) in this experiment, there are still considerably many participants making different choices. Table 5.3.1 shows the share of participants making different choices in the three treatments. From Table 5.3.1 we find:

1. Although choosing \emph{B} generates higher expected return (4\% for \emph{B} vs. 3\% for \emph{A}), many participants still choose \emph{A} with a high frequency (30\% to 40\%).

2. Although choosing \emph{A} generates strictly positive returns, and is therefore a dominating strategy to choosing neither of the funds, there are still a few participants choosing neither for some of the times (0.1\% to 1\%).

3. The fact that more people in treatment O choose \emph{B} compared to treatment N
suggests that people pay more attention to the gross return instead of net return. (The difference between the choice of B in treatment N and treatment O is significant at 5% level according to Mann Whitney Wilcoxon test.)

4. The fact that more people in treatment F choose B compared to treatment O suggests that charging a fee in the form of front end load fee itself is not more discouraging than charging it in the form of operation fee. (Although the difference between the choice of B in treatment F and treatment O is not significant at the 5% level according to Mann Whitney Wilcoxon test.)

5. There are more subjects choosing fund B in treatment F compared to other treatments already in period 1, which suggests that the subjects do not hesitate a lot before taking the decision to choose the fund with a substantial front end load fee.

In all treatments the fraction of subjects choosing B is higher in the second 15 periods compared to the first and third 15 periods. Theoretically this should not happen because the ex ante expected return of fund A and B do not change. One possible reason is that the realized return of B happens to be less than the return of fund A more frequently.

![Table 5.3.1: Fraction of participants/times choosing different options in each treatment.](image-url)
in the second 15 periods (in 6 out of 15 periods) compared to the first (in 3 out of 15 periods) and third 15 periods (in 5 out of 15 periods). This suggests that the individual investment decisions are influenced by the realized past return information, although it should not be used under optimal decisions. We will discuss the influence of past return information on individual decisions in this experiment in detail in section 3.5.

5.3.2 Heterogeneity in Individual Choice

Figure 5.3 shows the fraction of choice of B against all choices by each individual in different treatments. This graph helps us to see whether there is heterogeneity in individual participants’ propensity for each choice. In other words, it helps to illustrate whether the relatively low choice rate of B is caused by some individual who choose B really rarely, or every individual contributes a little to it.

We see that in treatment N and O, individuals are similar to each other in making choice of B. Meaning that every individual generally chooses B with a little more than 50% of the chance. There are very few participants choosing B with close to 100% probability, but also very few choosing B with less than 40% of the chance. In contrast, in treatment F, many individuals choose B with almost 100% chances, while there are also individuals who almost never choose B. A Kolmogorov-Smirnov test can not reject the null hypothesis that the distribution functions of individual frequencies of choice of B are the same for treatment N and O, but reject the null that the distribution functions are the same for treatment N and F, or treatment O and F at the 5% level.

This result shows there is a lot heterogeneity in individual choice when participants are faced with a salient fee. Most of them decide to choose B from the very beginning and do not switch to other options at all, while very few of them decide to stay away from B for most of the periods. To some extent, the front end fee is like a tool for

Among the 14 subjects who choose fund B for more than 90% of the time, only 8 of them choose B for all periods (100% of the time). That means there are still 6 of them who switch away from B at some period of time, which is not an efficient decision.
Figure 5.3: The histogram of individual choices of B. The horizontal axis represents the percentage of choice of fund B by each subject, and the vertical axis represents the percentage of subjects who choose fund B at this frequency.
some participants to commit themselves to a decision with a long horizon. While some others are “scared out" and stay with fund A, which is safer, but generates lower expected return.

Table 5.3.2 shows the number and percentage of subjects who always choose one fund in each block of 15 periods, and all three blocks of periods. We see that both the numbers of subjects who always choose fund A and those who always choose B are the highest in treatment F, and these numbers are generally very small in treatment N and O, which confirms that subjects are more reluctant to switch to another fund in treatment F.

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Always Choosing A</th>
<th>Always Choosing B</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number of Subjects</td>
<td>Percentage</td>
</tr>
<tr>
<td><strong>Treatment N</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>First 15 Periods</td>
<td>0</td>
<td>0.00%</td>
</tr>
<tr>
<td>Second 15 periods</td>
<td>0</td>
<td>0.00%</td>
</tr>
<tr>
<td>Third 15 Periods</td>
<td>0</td>
<td>0.00%</td>
</tr>
<tr>
<td>All Periods</td>
<td>0</td>
<td>0.00%</td>
</tr>
<tr>
<td><strong>Treatment O</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>First 15 Periods</td>
<td>0</td>
<td>0.00%</td>
</tr>
<tr>
<td>Second 15 periods</td>
<td>0</td>
<td>0.00%</td>
</tr>
<tr>
<td>Third 15 Periods</td>
<td>0</td>
<td>0.00%</td>
</tr>
<tr>
<td>All Periods</td>
<td>0</td>
<td>0.00%</td>
</tr>
<tr>
<td><strong>Treatment F</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>First 15 Periods</td>
<td>0</td>
<td>0.00%</td>
</tr>
<tr>
<td>Second 15 periods</td>
<td>2</td>
<td>5.71%</td>
</tr>
<tr>
<td>Third 15 Periods</td>
<td>3</td>
<td>8.57%</td>
</tr>
<tr>
<td>All Periods</td>
<td>0</td>
<td>0.00%</td>
</tr>
</tbody>
</table>

Table 5.3.2: The number of percentage of the subjects who always choose one fund in each block of 15 periods and all three blocks of 15 periods.

### 5.3.3 Frequency of Switching

One possible explanation for why front end load fee is not that discouraging as expected is that front end load fee may generate a “lock in" effect. Once a participant invested in the fund that charges a front end load fee, although it is a sunk cost for future decisions, he or she may still be reluctant to switch to other options. We count the frequency of
switching (a switching is counted when a participant chooses differently in one period compared to the last period) in the three treatments. Because the number of observation is somewhat different in the treatments, we use the average frequency of switching per subject per period as the measure.

<table>
<thead>
<tr>
<th>Peroids</th>
<th>N</th>
<th>O</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>First 15</td>
<td>0.28</td>
<td>0.20</td>
<td>0.22</td>
</tr>
<tr>
<td>Second 15</td>
<td>0.32</td>
<td>0.30</td>
<td>0.18</td>
</tr>
<tr>
<td>Third 15</td>
<td>0.27</td>
<td>0.20</td>
<td>0.12</td>
</tr>
<tr>
<td>All periods</td>
<td>0.29</td>
<td>0.23</td>
<td>0.17</td>
</tr>
</tbody>
</table>

Table 5.3.3: Frequency of Switching per Subject per Period in different treatments/phases.

Table 5.3.3 shows the frequency of switching per subject per period in this experiment. It is clear that the frequency of switching is highest in treatment N, and lowest in treatment F. Together with the findings in the last section, it is clear that the front end load fee is the key element that makes people stick fund B once they have chosen it. A Mann Whitney Wilcoxon test indicates that the difference between the frequency of switches across treatments is significant at the 5% level. Within each treatment, the difference between the number of switches across different phases (first, second or third block of 15 periods) is usually not significant except for treatment F where the frequency of switching is significantly smaller in the third 15 periods compared to the first and second 15 periods. This finding suggests subjects learn to switch less frequent in treatment F in order to avoid the front end load fee when entering fund B again.

Figure 4.8 shows the empirical cumulative distribution function of the number of switches by each individual in each treatment. The experiment consists of 3 times 15 periods, so the maximum number an individual can switch is $3 \times 14 = 42$ times. We find a lot of differences between the number of switches across treatments. There is almost an order of first order stochastic dominance. The number of switches by each individual is generally smallest in treatment F, and largest in treatment N.

We also consider a type of switching that is extremely inefficient in treatment F. In
every 15 periods, if a subject switches to fund B from other options after the 8th period (period 8 in first 15 the periods, period 23 in the second 15 periods, and period 38 in the third 15 periods), that is surely a mistake, because the gain in choosing fund B in later period can not cover the front end load fee paid. We find the number of subjects making such a mistake is 11 (out of 35) in the first 15 periods, 8 in the second 15 periods, and 2 in the third periods, which shows a strong learning effect by the subjects in order to avoid a large front end load payment.

### 5.3.4 Earnings

Table 5.3.4 shows the average earnings of individual subjects in different treatments. We can see that although people choose fund B with higher frequency in treatment F, both the average and median earnings in this treatment are still the lowest because of some inefficient switching decisions in the early periods. The earnings in treatment F are
significantly lower than the other two treatments in the second 15 periods at 5% level according to Mann-Whitney-Wilcoxon test, and there are no significant differences in earnings between treatments in other periods. The difference between the median earnings is smaller than the difference in average earnings across treatments, which suggest that the low average earnings in treatment F are mainly caused by some participants who keep choosing A or switch too much.

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Treatment N</th>
<th>Treatment O</th>
<th>Treatment F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Period</td>
<td>Mean</td>
<td>Efficiency</td>
<td>Mean</td>
</tr>
<tr>
<td>First 15</td>
<td>1653.86</td>
<td>83.70%</td>
<td>1682.81</td>
</tr>
<tr>
<td>Second 15</td>
<td>1503.22</td>
<td>82.10%</td>
<td>1493.52</td>
</tr>
<tr>
<td>Third 15</td>
<td>1593.08</td>
<td>82.93%</td>
<td>1579.89</td>
</tr>
<tr>
<td>All Periods</td>
<td>1583.39</td>
<td>82.90%</td>
<td>1585.41</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Period</th>
<th>Median</th>
<th>Efficiency</th>
<th>Median</th>
<th>Efficiency</th>
<th>Median</th>
<th>Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>First 15</td>
<td>1574.69</td>
<td>79.69%</td>
<td>1708.93</td>
<td>86.48%</td>
<td>1637.8</td>
<td>82.88%</td>
</tr>
<tr>
<td>Second 15</td>
<td>1481.18</td>
<td>80.89%</td>
<td>1493.53</td>
<td>81.57%</td>
<td>1516.51</td>
<td>82.82%</td>
</tr>
<tr>
<td>Third 15</td>
<td>1661.15</td>
<td>86.47%</td>
<td>1567.78</td>
<td>81.61%</td>
<td>1606.76</td>
<td>83.64%</td>
</tr>
<tr>
<td>All Periods</td>
<td>1539.28</td>
<td>80.59%</td>
<td>1567.78</td>
<td>82.08%</td>
<td>1567.94</td>
<td>82.09%</td>
</tr>
</tbody>
</table>

Table 5.3.4: Average individual earnings in different treatments/phases. The earnings are in terms of points.

Figure 5.5 shows the empirical CDF of individual earnings in different treatments. We observe more heterogeneity in individual earnings in treatment F compared to treatments N and O. Note that the payoff for always choosing neither is 1000 points. The payoff for always choosing $B$ is between 1500 and 1900 points for each of the three blocks of 15 periods. The payoff for always choosing $A$ is between 1300 and 1600 points for each of the three blocks of 15 periods. The detailed total return rate for different scenarios is shown in Table ???. Therefore treatment F has not only the largest number of subjects who earn almost the maximum, but also the largest number of subjects who earn even less than the initial wealth.
Table 5.3.5: The total return rate for different scenarios in each block of 15 periods. The second and third columns show the expected return rate for always choosing A and B. The fourth and fifth columns show the actual total return for always choosing A and B. The final wealth in each scenario equals the initial wealth (1000 points) multiplied by the total return rate.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.5126</td>
<td>1.7317</td>
<td>$1.01^8 \cdot 1.05^6 = 1.4511$</td>
<td>$1.02^2 \cdot 1.06^7 = 1.8653$</td>
</tr>
<tr>
<td>2</td>
<td>1.5126</td>
<td>1.7317</td>
<td>$1.01^7 \cdot 1.05^7 = 1.5086$</td>
<td>$1.02^{10} \cdot 1.06^4 = 1.5390$</td>
</tr>
<tr>
<td>3</td>
<td>1.5126</td>
<td>1.7317</td>
<td>$1.01^{10} \cdot 1.05^4 = 1.3427$</td>
<td>$1.02^8 \cdot 1.06^9 = 1.6620$</td>
</tr>
</tbody>
</table>

5.3.5 Influence of Past Performance

We wonder whether the high frequency of choice of fund A in the experiment can be explained by the fact that although fund B has higher expected return, fund A can generate higher realized return due to the noise term $\epsilon_t$. Participants may be affected by the higher realized return by fund A in some periods, and choose A in the next period.

Figure 5.6 plots the time series of the actual fraction of subjects choosing B against the binary variable that indicates whether the realized return of B is larger than A in the last period.
There is a clear pattern that the fraction of subjects choosing B increases when B generates higher return in the last period, which suggests that people are driven by past performance, even though they should ignore it in order to make an optimal decision.

We estimated two discrete choice models similar to Brock and Hommes (1997):
\[
\text{Pr} (\text{choice} = B, t) = \frac{e^{\beta_0 + \beta_1 (r_{B,t-1} - r_{A,t-1})}}{e^{\beta_0 + \beta_1 (r_{B,t-1} - r_{A,t-1})} + 1}, \tag{5.4}
\]

Coefficient \(\beta_0\) represents a predisposition effect for choosing fund B. If \(\beta_0\) is positive infinity, all subjects choose fund B when there is no difference in the past return of fund A and B. If \(\beta_0 = 0\), the fraction of subjects choosing fund A and B will be half-half when there is no difference in the past return of A and B. If \(\beta_0\) is minus infinity, all subjects choose fund A if there is no different in the past return of fund A and B. If all subjects make optimal decision, the estimated \(\beta_0\) should be positive infinity, and we expect the estimated \(\beta_0\) to be a positive number. \(\beta_1\) is the intensity of choice parameter. We expect \(\beta_1\) to be positive, which means if B generates higher return than A in the last period, more people will choose fund B in this period. Table 5.3.6 shows the estimated coefficients of the models. We see all the coefficients have the expected sign.

<table>
<thead>
<tr>
<th>Treatment</th>
<th>N</th>
<th>O</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\beta_0)</td>
<td>0.3798</td>
<td>0.5689</td>
<td>0.7956</td>
</tr>
<tr>
<td>p-value</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>(\beta_1)</td>
<td>14.2289</td>
<td>9.7480</td>
<td>6.6277</td>
</tr>
<tr>
<td>p-value</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>McFadden’s (R^2)</td>
<td>0.0327</td>
<td>0.0145</td>
<td>0.0070</td>
</tr>
</tbody>
</table>

Table 5.3.6: Estimated coefficients of the logit model in different treatments.

The results of the estimations confirm that the fund choice decision in this experiment is heavily driven by past performance, although such information should be irrelevant for optimal decisions. From Figure 5.7 we see that the fitted data capture the pattern of the movement in the experimental data.

There are several empirical and experimental works that estimate the discrete choice model similar to Brock and Hommes (1997) before us, e.g. Boswijk et al (2007), Anufriev and Hommes (2012a, 2012b), Anufriev et al (2012) and Bao et al (2012). One important purpose of these studies is to make estimation of the intensity of choice parameter \(\beta\), which is similar to the coefficient \(\beta_1\) in Equation 5.4. The estimated/calibrated \(\beta\) in former
Figure 5.7: The actual and fitted fractions of subjects who choose B. The squares correspond to the experimental data, and the triangles to the fitted time series by model (5.4)

papers is usually around 0.4. In our experiment the estimated coefficient is considerably larger. One reason for this difference is that the measure of fitness in our paper (return rate) is very small, and the estimated coefficient can be larger due to scaling effect. Therefore we estimate a normalized model that has exactly the same specification with
Brock and Hommes (1997) where we divide the fitness measure by \( r_{A,t-1} \):

\[
f_{B,t} = \frac{e^{\beta \frac{r_{B,t-1}-1}{r_{A,t-1} - 1}}}{e^{\beta \frac{r_{B,t-1}-1}{r_{A,t-1} - 1}}} + 1.
\]  

(5.5)

This normalization helps us to compare the results from different experiments. The estimation results are shown in Table 5.3.7. We see that the new estimated intensity of choice \( \beta \) is around 0.2, which is closer to the estimated \( \beta \)'s in former studies. It is reasonable for us to have a smaller \( \beta \) here, because subjects in our experiment have more information, and the rational decision indicates that their decision should not be affected by past performance. A smaller but significant \( \beta \) suggests that the subjects are not completely irrational, and the choice driven by past performance is a robust stylized fact in this kind of environment. Figure 5.8 shows the fitted fraction of people choosing B against the experimental data. We see this model also provides a very good fit to the data.

<table>
<thead>
<tr>
<th>Treatment</th>
<th>N</th>
<th>O</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta )</td>
<td>0.2437</td>
<td>0.1977</td>
<td>0.2198</td>
</tr>
<tr>
<td>p-value</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>Likelihood</td>
<td>-593.31</td>
<td>-498.70</td>
<td>-935.32</td>
</tr>
</tbody>
</table>

Table 5.3.7: Estimated coefficient of the normalized logit model for different treatments.

### 5.4 Conclusion

We consider the relationship between mutual fund choice and the structure of the fees by running laboratory experiments where subjects choose between two experimental funds. The subjects know that the expected return of one fund is higher than the expected return of the other, and the standard deviation of the return of the two funds is the

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Because the model does not include an intercept, it is not possible to calculate McFadden’s R Squared. We provide the likelihood directly.
same. Therefore the optimal choice rule should be always choosing the fund with higher expected return.

We find that participants do not always choose the fund with higher expected return. Instead, the fund choice decision is heavily driven by past performance of the funds. A
simple discrete choice model can capture the qualitative feature of the experimental data. When the fund with higher expected return charges a fee while the other does not, the fraction of people choosing this fund is not lower when the fee is charged in terms of front end load than when it is charged in terms of operation expense.

The findings from this experiment suggest that the bounded rationality in mutual fund choice in Choi et al (2010) cannot be easily mitigated by experience and learning. It is therefore probably desirable for the government and regulation authorities to invest effort to enhance the level of financial literacy in society.

We are aware that several authors documented the fact that it may happened that subjects in financial markets experiments or even simpler experiments are in lack of game form recognition as for instance in Chou et al. (2009). These authors show that, to a surprising degree, subjects seem to have little understanding of the experimental environment in which they are participating. They suggest that in order to gain control over the understanding of the experimental procedures, isomorphic games should be adapted to each type of subject population. This has been also underlined by Kirchler et al. (2012), who showed that running the usual experiment with a different context ("stocks of a depletable gold mine" instead of "stocks") significantly reduces mispricing and overvaluation as it reduces confusion. In our experiment, we do not fond any evidence of lost of game form recognition control. Indeed, control questions and after-experimental questionnaires show that our subjects fully understood the experimental procedures. In fact, the form in which instructions have been presented to them is coherent with a consonance principle since those students do take investment decisions on regular basis in their other (finance) classes in the business school.

We find that although a front end load fee is more salient than an operation fee, it is not more discouraging to investors as a fee structure per see. When the fund with a fee has higher expected returns, charging a fee in the form of front end load fee generates a "lock in" effect that prevents investors from switching to another fund. This may have some
implications for marketing strategy of funds. For example, if a fund manager believes that his fund is intrinsically better than those of others, it may be better for him to charge a front end load fee, although charging an operation fee is currently more popular in the industry.

There are several ways to extend the current study. One possibility is to vary the fee rate of fund B to see whether people are more sensitive to (the same amount of) changes in the front end load fee than the operation fee, as in Barber et al (2005). It will be interesting if one can reproduce this stylized fact in financial markets in the lab, and estimate the fee-elasticity using experimental data to make some comparison with empirical work.

5.A Appendix

5.A.1 An Example of Translated Experimental Instructions

Experimental instructions - Treatment N

General information In this experiment you are asked to make subsequent investment decisions. You will start with 1000 points which you can invest. In every subsequent period you will have the possibility to reinvest your accumulated points. In every period you can only invest all of your points in fund A, all of your points in fund B, or invest in neither of the two funds. Your earnings from the experiment will depend upon how well your investments will do.

The funds Fund prices The price of fund A is $P_A(t)$ in period $t$, and the price of fund B is $P_B(t)$ in period $t$. Over time prices of the funds grow in the following way. The price of fund A in period $t+1$ is equal to $(1 + g_A)$ times the price of fund A in period $t$, that is

$$P_A(t + 1) = (1 + g_A) \times P_A(t).$$
The growth rate $g_A$ can only take one of two values. It is either equal to 0.05, or it is equal to 0.01. Both values are equally likely to occur (that is, both occur with the probability equal to 0.5). The history of values of $g_A$ does not influence the probability of either value occurring.

Similarly, the price of fund B grows with growth rate $g_B$, which could either be 0.06 or 0.02. Again both values are equally likely to occur. The price of fund B in period $t$ therefore is

$$P_B(t + 1) = (1 + g_B) \times P_B(t).$$

Prices of the two funds do not influence each other. Moreover, your decisions will not influence the price of the two funds.

Example: Suppose the price of fund A is equal to 50 in period 1, and the growth rate in period 1 is equal to 0.05. In that case we have $P_A(2) = 1.05 \times 50 = 52.5$. If the growth rate in period 2 is given by 0.01 then the price in period 3 will be given by $P_A(3) = 52.5 \times 1.01 = 53.03$, and so on.

Investing If you invest your points in one of the two funds, the number of points you have will grow. For example, suppose you invest your 1000 points in fund A in period 1, when the price of fund A is $P_A(1) = 50$, and you keep your points in fund A until period 6. By then the price of fund A has grown to, for example, $P_A(6) = 60$. Then your points will have increased up to

$$1000 \times \frac{60}{50} = 1200.$$  

If you then decide to invest these points in fund B for the next two periods and, for example $P_B(6) = 56$, $P_B(7) = 59$ and $P_B(8) = 61$, your total number of points at the end of period 8 will be equal to

$$1200 \times \frac{61}{56} = 1307.14.$$  

by period 10. Note that your points will remain constant in the periods in which you
invest in none of the two funds.

Your task The experiment consists of three parts of 15 periods.

In each part you start out with 1000 points, and you can increase the number of points by investing in the two funds A and B. In every period you have three options. Either to invest all of your points in fund A, or to invest all of your points in fund B, or to invest your points in neither fund. You are allowed to switch between funds as often as you want to, but you do not have to.

After the first 15 periods are finished, the experiment will be restarted. Your initial points will be reset to 1000 points and the prices of funds A and B will be reset to their initial values again. The values that the growth rates of the two prices can take are the same again (0.05 and 0.01 for fund A, with equal probability, and 0.06 and 0.02 for fund B, also with equal probability). Because these values are random, the actual growth rates in this second part of 15 periods will, most likely, be different for the actual growth rates in the first part of 15 periods.

After the second part of 15 periods, the experiment will be restarted in the same way as described above for another 15 periods.

Information: The information that you have at the beginning of time t, when you have to make your investment decision for period t, consists of the current prices, all past prices and all past growth rates of both funds. The current prices are shown in the top part of the computer screen. Both past prices and past growth rates are shown in a table on the computer screen. The prices of the funds are also shown in a graph on the screen. Moreover, we show your total accumulated (from the beginning of the current part) number of points in the top part of the computer screen.

Earnings After the experiment you are paid out according to only one of the three parts. For which part you are paid is determined randomly, and with equal probability.
You will be paid for the total number of points, and for each point you will receive 1 euro cent. For example, suppose in the first part your initial number of points increased from 1000 to 1800 points, in the second part your number of points increased from 1000 to 1400 points, and in the final part your number of points increased from 1000 to 1600 points. Then you will earn 18 euros if you are paid according to the first part, and 14 euros if you are paid according to the second part and 16 euros if you are paid according to the final part.

5.A.2 Control Questions with Answers

Treatment N

1. Suppose that in the current period the price of fund A is 70 and the price of fund B is 74.1. You have 700 points in the current period and you choose to invest in fund A. Suppose that in the next period the price of funds A and B turned out to be 73.5 and 76.3, respectively. How many points do you have at the beginning of the next period? (735)

2. You have 1100 points at the beginning of the current period and want to invest in fund B. Would your investment decision from the previous period (i.e., in which fund you invested previously) matter for the number of points you will earn? (No)

Treatment O

1. Suppose that in the current period the price of fund A is 70 and the price of fund B is 74.1. You have 700 points in the current period and you choose to invest in fund A. Suppose that in the next period the price of funds A and B turned out to be 73.5 and 76.3, respectively. How many points do you have at the beginning of the next period? (735)

2. Suppose you have 600 points and you invest your points in fund B whose price in
the current period is 57. Fund B charges a fee of 1%. How much fee would you pay for this period? (6)

3. You have 1100 points at the beginning of the current period and want to invest in fund B. Would your investment decision from the previous period (i.e., in which fund you invested previously) matter for the number of points you will earn? (No)

Treatment F

1. Suppose that in the current period the price of fund A is 70 and the price of fund B is 74.1. You have 700 points in the current period and you choose to invest in fund A for which there is no fee. Suppose that in the next period the price of funds A and B turned out to be 73.5 and 76.3, respectively. How many points do you have at the beginning of the next period? (735)

2. Suppose you invested in fund A in the last period, you have 1000 points at the beginning of this period and want to invest in fund B in this period. Fund B charges a fee of 13%. How much fee would you pay? (130)

3. Recall that fund A does not charge a fee, and fund B charges a fee of 13%. You have 1100 points at the beginning of the current period and want to invest in fund B. Would your investment decision from the previous period (i.e., in which fund you invested previously) matter for the number of points you will earn? (Yes)