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Do actively managed mutual funds beat the market?
A randomized procedure using Monte Carlo simulation

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Abstract

The aim of the thesis is to examine if the efficient market hypothesis applies to the Swedish mutual fund market, and thereby determine whether actively managed funds in Sweden beat the market or not. In order to do so I constructed a Monte Carlo simulation of the Stockholm stock exchange that produced random portfolios following a set of investment constraints. A series of comparisons between the actual mutual funds and the random portfolios showed that active management did not create any excess returns above what could be explained by luck. No sign of superior stock selecting abilities or timing was found.

Table of contents

Abstract	1
Table of contents	2
1. Introduction	4
1.1 Background.....	4
1.2 Purpose of the thesis.....	4
1.3 Delimitations	5
2. Theoretical framework	6
2.1 Relevant theories	6
2.1.1 The efficient market hypothesis.....	6
2.1.2 Critique of the efficient market hypothesis	7
2.1.3 Random walk theory	8
2.2 Earlier findings.....	9
2.2.1 Jensen finds no superior performance.....	9
2.2.2 Friend, Blume and Crockett get mixed results	10
2.2.3 Ippolito see superior performance.....	10
2.2.4 Elton <i>et al</i> prove Ippolito wrong.....	10
2.2.5 Malkiel finds survivorship bias	11
2.2.6 Carhart sees no persistence in results.....	12
2.2.7 A few ending words.....	12
3. Method	13
3.1 Hypothesis	13
3.2 Measurements	13
3.2.1 Indices.....	13
3.2.2 Peer groups.....	14
3.2.3 Random portfolios.....	14
3.3 Data selection.....	15
3.3.1 Time period	15
3.3.2 Fund data.....	15
3.3.3 Stock data	16
3.3.4 Other data	17
3.4 Monte Carlo simulation.....	17

3.5	Test variables.....	18
3.5.1	Annualized Average Return, R.....	19
3.5.2	The Information Ratio, IR	19
3.5.3	Risk-adjusted profitability index, PI.....	19
3.6	Concerns.....	20
4.	Empirical findings.....	21
4.1	Random portfolio selection.....	21
4.1.1	Randomly weighted portfolios	21
4.1.2	Proportionally weighted portfolios	23
4.2	Constructing an artificial benchmark	24
4.3	Opportunity groups	24
4.4	Combined p-values.....	26
4.5	Picking a winner.....	27
4.6	Is it all luck?	27
5.	Concluding remarks	29
	References.....	30
	Appendix	33

1. Introduction

1.1 Background

I find the idea of an efficient market and its implications for investing interesting. If the market is efficient, then there is no way for investors to reliably beat it. The only way to increase expected returns is by taking on more active risk. This is also what almost every economist will tell you if you ask them. Most finance journals will tell you to diversify, buy and hold or to invest in an index fund. One economist went as far as to say that 'a blindfolded chimpanzee throwing darts at the stock pages could select a portfolio that would do as well as the experts' (Malkiel 2005: 1-2). Regardless of this, a large majority of the population put their money in the hands of managers that claim that they can beat the market.

If you take a look at some historic data of mutual funds, no doubt you will find that some funds have performed a lot better than other funds. Now, why is this? Is it because the managers of these funds have superior stock selecting skills or timing? If this were the case, then the odds are good that these funds will perform well in the future and might be a suitable place to put your savings in.

However, if the market is in fact efficient and if there is no sure way to raise expected returns except by taking on more active risk, then there is only one explanation left as to why some funds have performed better than the rest: The managers of those funds have been lucky when taking bets against the market. If this is the case, then the odds that those funds will perform well in the future just got a lot worse and those funds might not be such a good place to put your savings in.

1.2 Purpose of the thesis

A lot of people put their faith and money into actively managed funds in the hope for extra profit. The managers of these funds often declare that their goal is to beat the market and thereby create excess return through the use of information and superior skills. My purpose with this thesis is to examine if there is any proof to these claims. I will try to determine if

successful managers really possess superior stock selecting abilities or timing or if they have just been lucky. In order to do this I will employ the use of Monte Carlo simulation to create a representation of the managers' investments universe that will be used as a base for comparison.

1.3 Delimitations

I have studied 25 Swedish mutual funds during 2000-2009. This period is interesting since it contains both a bear and a bull period. All funds in the study are Swedish mutual funds that invest solely or primarily in the Swedish stock market at the Stockholm exchange. According to the Morningstar style box all included funds were of the style *large value*, *large blend* or *medium blend*. I will look only at traditional managers, i.e. those that take only long positions. Since my study is of active managers I will not include managers of index funds. Finally only funds that have existed for the entire period are included. Further constraining the characteristics of the funds would have brought the number of funds in the study below 25 which would be damaging from a statistical standpoint.

2. Theoretical framework

2.1 Relevant theories

This section features a presentation of the efficient market hypothesis and the random walk theory as they are central to this thesis.

2.1.1 The efficient market hypothesis

The theory regarding an efficient market is central to this study. In finance the term *efficient market* has a very precise meaning; it means that security prices fully reflect all information available. However this is a very strong hypothesis because unless the cost of acquiring information and trading were both zero there would be no incitement for investors to actually trade until all prices fully reflected all the information (Elton, Gruber, Brown & Goetzmann 2007). Therefore another definition is more commonly used, that 'prices reflect information until the marginal cost of obtaining information and trading no longer exceed the marginal benefit' (Elton *et al.* 2007: 400).

An economist closely related to the study of an efficient market is Eugene Fama. In 1970 he reviewed the literature on the efficient market model and suggested the following classifications: weak form tests, semi strong form tests and strong form tests (Fama 1970).

- **Weak form tests:** In its weak form the hypothesis states that current prices fully reflect all information contained in historical prices. The weak form tests are tests concerned with whether all information regarding historical prices is fully reflected in current prices (Fama 1970). In a later paper Fama (1991) broadened his definition of the weak form tests to include all tests that test for return predictability. If the weak form hypothesis is true technical analysis cannot be effective in creating higher returns than the market on average (Malkiel 1985).
- **Semi strong form tests:** The semi strong version of the hypothesis states that current prices fully reflect all publicly available information (including historical prices and everything else contained in the information set for the weak form test). Consequently semi strong tests are tests that investigate if the information

set containing all public information is fully reflected in the current prices (Fama 1970). Another term often used for this form of tests is *event studies* (Fama 1991). If the semi strong form of the hypothesis holds true neither technical nor fundamental analysis can be used to create excess return compared to the market or a buy-and-hold strategy (Malkiel 1985).

- **Strong form tests:** In the strongest form the hypothesis states that current prices fully reflect all available information, public and private. Strong form tests therefore investigate whether anyone at all can make excess profit (Elton *et al.* 2007). If this level of the hypothesis is true it would mean that everyone has access to what we normally call *insider information*. This form of the hypothesis is highly unlikely to be true as there are strict regulations concerning what information may be made publicly available. Fama himself points out that 'One would not expect such an extreme model to be an exact description of the world, and it is probably best viewed as a benchmark against which the importance of deviations from market efficiency can be judged' (Fama 1970: 414).

As I am interested in determining whether active fund managers possess any superior stock selecting abilities or timing, I am interested in the weak form (stock selecting ability) as well as in the semi strong form (timing) of the efficient market hypothesis.¹ I am not interested in the strong form since I do not believe that fund managers have access to insider information, which is supported by the study made by Jensen (1968). What is more, even if they did have access to private information they would be forbidden to act on it.

2.1.2 Critique of the efficient market hypothesis

For a long time the efficient market hypothesis was widely accepted by most financial economists. Still today it is the dominating view, but there have been those who have been critical of it. One such group are the behavioural economists. According to them the market is in fact not at all as rational as the hypothesis states.

¹ In reality I am only interested in the semi strong form, since at this level the hypothesis includes everything contained in the weak form too.

Richard Thaler (1980), a founder of the approach, claims that many economists make the mistake of believing that normatively based utility theory is in fact also descriptive theory, and as a result overestimate the rationality of consumers and investors. Thaler as well as Kahneman and Tversky (1979) argue that consumers are not rational in regard to risk as they treat gains different from losses and commit judgement errors. Furthermore they mean that these errors are systematic and predictable.

But if investors make systematic and predictable errors, can the market then be efficient? Yes, says Malkiel (2003) in his critique of the criticism against the efficient market hypothesis. He argues that a financial market is efficient as long as it does not allow investors to earn above average returns without accepting above average risk. Malkiel claims that a market can still be efficient even if many participants are quite irrational and even if volatility of the equities is higher than that of the underlying assets. Even so he does not believe that market pricing is always perfect and he admits that psychological factors may affect prices. But he still maintains that there is no way that investors can reliably exploit any irregularities or patterns that may exist.

If the market is efficient there should be no reliably way of beating the market. Instead the best bet would be to join the market by following an index or a buy and hold strategy. The same holds true even if consumers are irrational, at least if you believe in Malkiel's reasoning. Even Kahneman (see above), when asked what advice he would give an investor, answered: 'buy and hold' (Fox 2002).

2.1.3 Random walk theory

An idea closely related to the efficient market hypothesis is the *random walk theory*. According to Malkiel (2003) this idea states that stock prices follow a random walk so that each price change is unrelated to earlier prices. The idea behind it is that if all information is immediately incorporated into stock prices then tomorrow's stock price changes will only be related to tomorrow's news and not to historic news or price changes. As a consequence, since prices fully reflect all information available, anyone can obtain a rate of return as good as that of the experts simply by buying a well diversified portfolio at random.

If stock prices follow a random walk that means that fund performance is just the result of a chance process. Malkiel (1985) wrote that, in any situation that has an average, given that enough people are involved, some of them will beat the average. With the number of

active players in the investment industry it is not surprising that some of them have outperformed others.

Malkiel used a coin flipping contest as a metaphor. If you were able to constantly flip heads you would be declared the winner. With 1000 players, around 500 would be left after one flip. 250 would still be around after the second round, 125 after the third round and so on. There would probably even be one person left who managed to flip 10 out of 10 heads. It then follows that he or she was the best at the coin flipping game. If the players were not eliminated after flipping a tail, we would find quite a large number of players with eight or more heads out of ten: the expert tossers (Malkiel 1985). His point with this metaphor was that chance may well be the explaining factor behind superior fund performance.

2.2 Earlier findings

Here follows a brief summary over some of the most important earlier findings in regards to the efficient market hypotheses and mutual fund performance.

2.2.1 Jensen finds no superior performance

One of the first major studies on fund performance was carried out by Jensen in 1968. In his study he compared the results from 115 mutual funds in the period 1945-1964. He wanted to compare the funds not only with each other but also against an absolute standard. So he compared them against a market portfolio based on the companies in the *Standard and Poor composite 500 price index* for the same period. He also adjusted the results with regard to the systematic risk of the funds in question (Jensen 1968).

His results showed that the average alpha for the funds was well below zero. On average the funds earned 1.1% less per year than they should have, given their beta-value. This, according to Jensen, implied that the funds on average did not outperform a random buy and hold policy. Not even after Jensen had corrected the fund data to compensate for management expenses did the funds regain their commission fees. Nor could he see any evidence that any individual fund performed better than what would be expected from simple luck (Jensen 1968).

2.2.2 Friend, Blume and Crockett get mixed results

Friend, Blume and Crockett (as cited in Elton *et al.* 2007) took a slightly different approach in evaluating fund performance. They divided the funds into categories based on their risk. They did not select an index to compare the funds against but instead they used a procedure for generating random portfolios, of approximately the same risk level as the fund categories. They then used these random portfolios as benchmarks to compare the real funds with.

The results they found were conflicting. Equally weighted random portfolios outperformed the real funds at all risk levels. But at higher risks the real funds outperformed some of the random portfolios that had been proportionally weighted so as to reflect the outstanding value of the stocks in the market². This shows that it is important to compare the managers against the proper alternative (as cited in Elton *et al.* 2007).

2.2.3 Ippolito notices superior performance

One of few researchers that have found evidence that active mutual funds outperform a passive index is Ippolito (1989). He looked at 143 mutual funds during a period from 1965 to 1984, the period following that which Jensen studied. Like Jensen he compared the funds with the S&P500 index and studied the alpha values.

In the 1968 study, Jensen had found that out of 115 funds there were 14 funds with significantly negative alphas and 3 with significantly positive alphas (at a 95% confidence level). Ippolito saw the opposite in his own study. Out of his 143 funds, 4 had significantly negative alphas and 12 had significantly positive alphas. He also found that on average the funds in his study had a positive alpha of 0.81%. His conclusion was that active fund managers did create excess return in comparison with a passive index (Ippolito 1989).

2.2.4 Elton, Gruber, Das and Hlavka prove Ippolito wrong

Elton, Gruber, Das and Hlavka (1993) took a critical look at Ippolito's study in order to see if his rather controversial results were due to the use of an incorrect index. As mentioned, Ippolito had measured the funds against the S&P500, while during this period, fund

² Friend Blume and Crockett used two variants when creating the proportionally weighted portfolios. In variant 1 the odds of selecting any stock was proportional to its outstanding value, once selected the same amount of money was invested in each stock. In variant 2 the odds of picking any stock were the same, however once chosen the amount invested in it was proportional to its market capitalization.

managers likely also held funds outside it. Elton *et al.* simulated a manager with no stock selection skills, who formed a portfolio from stocks both within the S&P500 and outside of it. When measured against the S&P500, this hypothetical manager too got a strong positive alpha for the period. They then looked closer at the small stock index and found that it had a positive alpha of 10.06% during Ippolito's period. Assuming that fund managers held some small stocks outside S&P500 this alone would explain their positive alphas against it.

Using a multi-index model Elton *et al* found results similar to the ones Jensen had found in the earlier period. The average alpha that they calculated for the funds during 1965-1984 was in fact -1.59% and they found no significantly positive alphas but 21 significantly negative values. Like Jensen before them, they concluded that active managers did in fact not outperform passive indices. Furthermore they showed how important the choice of index is and that it might be important to include smaller stocks if the managers are thought to hold these in their portfolios.

2.2.5 Malkiel finds survivorship bias

A few years later another researcher, Malkiel (1995), took a look at the performance of mutual funds in 1971-1991. He was particularly concerned with the existence of survivorship bias in the sample and therefore used a slightly different approach than the authors mentioned above. Malkiel pointed out that a fund that had taken on a high risk naturally would have had a high probability of failure; while at the same time if it had survived it would have made excess returns. As the failing funds would have dropped out of the sample while the survivors remained, the average results for mutual funds over a longer time period would be overstated. To remove this bias he studied not only data for funds that were still alive at the end of the period. Instead, for every year he looked at the returns from all of the funds that had operated during that year.

What he found was that the degree of survivorship bias for the period was substantial. Over a 10 year period he saw a bias of 1.4% in average annual return when comparing all funds against only the surviving funds. His final conclusion was that 'securities markets are remarkably efficient' (Malkiel 1995: 571). Based on this, his recommendation for investors was to buy a low cost index fund – rather than to try to pick a successful fund manager.

2.2.6 Carhart sees no persistence in results

In 1997 Carhart undertook an immense study of data consisting of all equity funds between 1962 and 1993. He wanted to test for persistence in mutual fund performance to see if there was any evidence for superior stock selecting skill. To control for survivorship bias he employed a method similar to the one Malkiel had used. He also used a combination of two measurements to evaluate the performance of the funds: the often used Capital Asset Pricing Model and a 4-factor model of his own creation (Carhart 1997).

But even though he ran the data through both models he could not find any significant evidence to support the existence of superior stock selecting ability. He deduced that funds that had earned a higher one-year return did so not because they followed a good momentum strategy but rather because they by chance had happened to hold a large portion of the winning stocks. Furthermore he reached the conclusion that transaction costs use up any gains from following such strategies (Carhart 1997).

2.2.7 A few ending words

What I have presented so far is only a small selection of the writings on the topic. However the collection is fairly representative of the studies on the subject. As can be seen from this sample a majority of the studies so far give support to the efficient market theory and there are few economists who actually believe that actively managed funds on average outperform the market.

3. Method

3.1 Hypothesis

My null hypothesis and alternative hypothesis are as follows:

$$\begin{cases} H_0: \text{Active managers do not have superior stock selecting ability or timing} \\ H_1: \text{Active managers do have superior stock selecting ability or timing} \end{cases}$$

In order to test the hypothesis I needed relevant data of fund return and risk and an appropriate measurement for comparison.

3.2 Measurements

When evaluating fund performance it is common to use either indices or peer groups. Another way to measure performance is by comparing funds with randomly generated portfolios. Here follows a brief definition of how these measurements work and possible issues with using them.

3.2.1 Indices

A stock index is a measurement constructed from a certain set of underlying stocks; SIXPX for example is an index that represents the average exchange on the Stockholm stock exchange, adjusted for the investment constraints that apply to stock funds (Fondbolagens förening c. 2010).

Surz (1996) argues that indices, despite their popularity and common use, are very poor benchmarks. This is because most managers follow a specific investment style and these styles go in and out of favour over time. As a result the performance of a fund can look very good or bad when compared against the broad market, only because the style is in or out of favour. Also, managers tend to switch between different style groups over time. He sees one solution in tailoring specific indices for each manager, but this would require a lot of time and effort.

Burns (2004) too is critical of the use of indices. He reasons that any index will be hard to outperform when the largest assets in the index happen to do well and easy to outperform when these assets do poorly. He points out that as a result of this one could draw ridiculous

conclusions such as that during the 90's managers in general were bad, when in fact it was just the index that performed well in this period.

3.2.2 Peer groups

A peer group is a benchmark constructed from other funds that are of the same investment style. Because of this they can be used to compare managers of the same style with each other. They have an advantage over indices in that they can be used even for short periods.

Surz (1996) lists several issues with using peer groups. The classification of managers into specific style groups is a problem, as the group they are forced into might not be accurate for them. There is also likely to be survivorship bias in the sample group as only the surviving funds are in the sample group. To exemplify this he uses an analogy 'If only 100 runners out of a 1,000-contestant marathon actually finish, is the 100th the last? Or in the top 10 percent?' (Surz 1996: 26).

Burns (2004) too criticizes the use of peer groups for performance evaluation, due to the fact that it is impossible to determine if any manager in the group has any skill at all. He points out that it is possible that not a single manager in the group has any skill whatsoever and that the top ranked managers have just been the luckiest within the group.

3.2.3 Random portfolios

Surz (1996) suggests the use of what he calls a portfolio opportunity distribution as a solution. These opportunity distributions are a set of hypothetical portfolios created through Monte Carlo simulation. They are created from the same set of stocks that is believed to be the manager's investment universe. In this way the random portfolios will be a representation of all the portfolios that the manager could have invested in. Ideally, the opportunity set should be created through a careful study of the manager's investment universe and decisions. Finally using economic and statistic methods the manager's strategy could be properly evaluated in comparison with this distribution of random portfolios (Surz 1996). However, I should point out that his main purpose has not been to examine fund managers as a group but rather to evaluate individual fund managers.

Burns (2004) also suggests the use of random portfolios as the solution for evaluating performance. He argues that

If we could compare an investment manager's portfolio to all of the portfolios that might have reasonably been chosen, then we would have the best possible measure of how well the manager did over the time period in question (Burns 2009: first paragraph).

In his study he does not measure real managers' performance. Instead he creates 100 computer generated managers that possess skill. These managers are given useful information about the future that has been generated from real data and then perform a portfolio optimization based on this information. In order to evaluate the managers he also creates a large set of random portfolios that follow the same constraints as the managers do but lack skill. I have used a method very similar to the one used by Burns. I applied it, however, to real managers.

3.3 Data selection

3.3.1 Time period

The period selected for the study starts on January 1, 2000 and ends on January 1, 2009. The length of the time period was chosen with two things in mind. I wanted to minimize the randomness of the fund returns, so a long evaluation period was needed. At the same time the time period had to be limited so that survivorship bias was kept at a minimum. At times the period was divided into three sub periods of three years each, so that the funds could be studied during different market climates and also be tested for persistence in performance over time.

3.3.2 Fund data

I have looked at data from 25 Swedish mutual funds. The funds were all found at the Morningstar site (Morningstar 2009). I selected the funds using these criteria:

- Only funds who invest solely or primarily in Swedish stocks were included. No funds that invest more than 10% outside the Swedish stock market were included.
- Funds that did not exist for the entire period were not included (unfortunately this might have created survivorship bias in the fund sample).
- Any fund profiling itself as an index fund was removed (as the purpose of the study was to evaluate actively managed funds).

- No hedge funds were included, only traditional ones (long only).
- Only funds classified as either large blend or medium blend according to Morningstar were selected (although at a later date all funds were classed as large value).
- Funds that donate a percentage to charity were not included, as their Net asset value (NAV) is calculated after the donations.

An employee at Morningstar kindly sent me NAV-series for these 25 funds. I extracted monthly data from these series that were used to represent the funds. Additionally I collected data of management fees for each fund in 2009. Assuming that these data were representative of the historic management fees as well, I calculated an alternative set of NAV-series putting back the management fees. This set will be referred to as 'including management fees' throughout the rest of the paper.

3.3.3 Stock data

To construct the random portfolios I needed a set of stocks. The database of Thomson Reuters Datastream (found in the Finance lab at the University of Lund) was used in collecting stock data for 231 stocks during the period 2000-2009. The stocks were selected according to these criteria:

- Only stocks listed at the Stockholm market exchange were selected.
- Only stocks listed in Swedish currency were included.
- Stocks with a base date later than January 1, 2000 were excluded.
- Only stocks that still exist today were included (this may cause survivorship bias in the stock sample).

Monthly data series for the market price of each stock were collected. Data of the number of shares outstanding at the start of the period were also collected. Multiplying number of shares with the stock price yielded the market capitalization for each stock at the starting date. Finally, these 231 stocks were used as a representation of the actual market.

3.3.4 Other data

Data for the Swedish 1-month T-bill, SSVX 1M, was taken from the home page of the central bank of Sweden (Riksbanken 2010). These data was used as a representation of the risk free rate. Series of a few different price indices were also downloaded using the Reuters Datastream database mentioned in the previous section.

3.4 Monte Carlo simulation

To test my hypothesis I would have preferred to evaluate the managers against all possible investment decisions that they could have made. However, since this is not possible I have instead used Monte Carlo simulation. Here follows a short definition of what this is.

Like regression analysis, Monte Carlo simulation is a general term that has many meanings. The word "simulation" signifies that we build an artificial model of a real system to study and understand the system. The "Monte Carlo" part of the name alludes to the randomness inherent in the analysis: Monte Carlo simulation is a method of analysis based on artificially recreating a chance process (usually with a computer), running it many times, and directly observing the results (Barreto & Howland 2006: 215-216).

The program I used for my simulation was Microsoft Excel. Using real data for stocks I created an artificial model representing the investment universe of the funds. Through a chance process, using Excel's rand() function³, two types of random portfolios were created from this universe. This chance process was then recreated 1000 times through the use of software from Barreto & Howland (2006).

The first type of random portfolios created I labelled as *randomly weighted random portfolios*. The name reflects the fact that they were simulated with almost no restrictions on the stock composition. The only restriction used was that no individual asset was allowed to amount to more than 5% of the total value of the portfolio at creation. Each asset was drawn at random from the list of stocks and assigned a weight between zero and 0.05. This process was repeated until the sum of weights equalled one⁴. The purpose of the 5% restriction was to create well diversified portfolios that a manager could actually hold. As

³ The Excel rand() function is according to Benninga 'a respectable random-number generator' (Benninga, 2008: 745).

⁴ In reality the last weight drawn would most likely increase the sum of weights to a value slightly higher than one and therefore had to be decreased so that the total sum was exactly one. In other words once the last asset had been found its weight was predetermined and not random.

expected the average portfolio held 40 stocks. The minimum number of stocks in any portfolio was 32 stocks and the maximum 55 stocks. This should be enough for a diversified portfolio (Statman 1987).

The second type of random portfolios created I called *proportionally weighted random portfolios*. As the name indicates more restrictions were used in the creation of these portfolios. This time I attempted to reproduce more closely the investment universe and style of the real managers, which meant using the following constraints.

- The average number of stocks in each portfolio was set to the same average as that of the real funds, which was 54 stocks (The minimum number of stocks held by any random portfolio was 18 and the maximum 92).
- The maximum weight of any individual asset was set at 10%.
- The odds of selecting each stock were the same, but once selected the amount invested in each asset was proportional to the market capitalization of that asset (as long as the rule of max 10% was obeyed). This meant that the weights of the assets were no longer drawn at random.
- A risk free asset represented by the 1-month T-bill was included. Each portfolio invested randomly in it. Its weight was drawn at random like with the randomly created portfolios. On average the portfolios invested 2.5% of their capital in the risk free asset.

The two types of random portfolios had one crucial thing in common: They both followed a basic buy and hold strategy.

3.5 Test variables

There are many ways to measure the performance of a portfolio. One of the most common is the Sharpe ratio. The historic Sharpe ratio as presented by Sharpe (1994) measures the risk adjusted return of a portfolio in relation to the volatility of the portfolio return.

However, the ratio has been criticized for not working as intended in periods of negative return, because volatility in these periods will actually raise the ratio (Scholz 2007). As my study period as a whole suffers from negative returns I decided not to use the Sharpe ratio.

3.5.1 Annualized Average Return, R

A funds average return is one of the first things to study when measuring performance. However a manager is not evaluated solely by his or her ability to create excess returns but also by the ability to keep risks at a minimum. Therefore average return is only suitable as a performance measure if the funds being measured have a very similar risk level, see for Example Elton *et al* (2007). When calculating return I use arithmetic returns.

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$$

3.5.2 The Information Ratio, IR

As pointed out, the information ratio is similar to the Sharpe ratio. The difference lies in that it does not measure a portfolio in relation to the risk free return; instead it measures it against any benchmark.⁵

$$IR = \frac{R_p - R_b}{\sigma}$$

The Information ratio can easily be converted into a t-statistic for hypothesis testing by multiplying it by the number of observations used for the calculation. As with the Sharpe Ratio, the Information ratio is hard to interpret when returns are negative (Truman 2003).

3.5.3 Risk-adjusted profitability index, PI

Another measure that I used is one similar to the one suggested by Lisi (2008). This is a form of risk-adjusted profitability index, where σ_b is the volatility of a benchmark.

$$PI = \frac{P_t}{P_0} \times \frac{\sigma_b}{\sigma}$$

As can be seen from the formula, it is closely related to the holding period return. The difference is that the initial investment is never subtracted from the result and as such the index will always be positive. Using this measure solved the problem discussed earlier regarding volatility in periods of negative return.

⁵The non annualized Information ratio can be transformed into an annualized Information ratio by multiplying it by the square root of observations per year, in the case of monthly data it should be multiplied by $\sqrt{12}$.

3.6 Concerns

I would like to point out a few concerns regarding the method:

- One problem is the classification of funds into style groups. I selected the funds from the Morningstar home page in November 2009. Back then, 18 of the funds in my sample were labelled as large blend and the remaining 7 as medium blend. A few months later when I studied the same funds at Morningstar they had all been changed to large value. This made the classification problematic and nicely illustrates what Surz (1996) said about how hard it can be to fit a fund into one of these categories.
- As only still active stocks were used to construct the random portfolios there is an obvious risk of survivorship bias. Likewise there is a risk of survivorship bias in the fund group as only funds that still existed were included in the study. Unfortunately there is no exact way for me to determine which of the two effects that is the larger one. Hopefully the amount of inactive funds is proportional to the amount of inactive stocks.
- Another issue could be that a buy and hold strategy was used in creating the random portfolios. A more accurate comparison could have been made if the random portfolios were given the ability to trade during the study period. This however lies outside the scope of this thesis.

4. Empirical findings

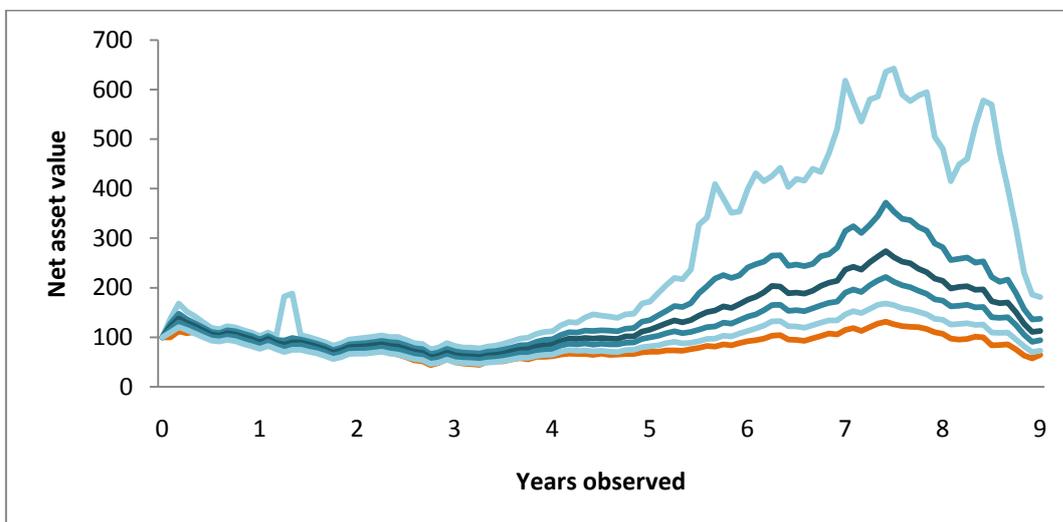
4.1 Random portfolio selection

The output from the Monte Carlo simulation was a thousand randomly weighted random portfolios and a thousand proportionally weighted random portfolios, each represented by its Net Asset Value-series. I now had to make sure that the model was working as intended by examining these portfolios.

4.1.1 Randomly weighted portfolios

I constructed quantiles from the randomly weighted portfolios to compare against the real funds. Figure 1 is a representation of the randomly weighted portfolios when compared to an average of the real funds. As can be seen from looking at the figure, the real funds were severely outperformed by the randomly weighted portfolios.

Figure 1: Randomly weighted portfolio quantiles, 5%, 25%, 50%, 75%, 95% (in blue) and the actual fund average (in orange).

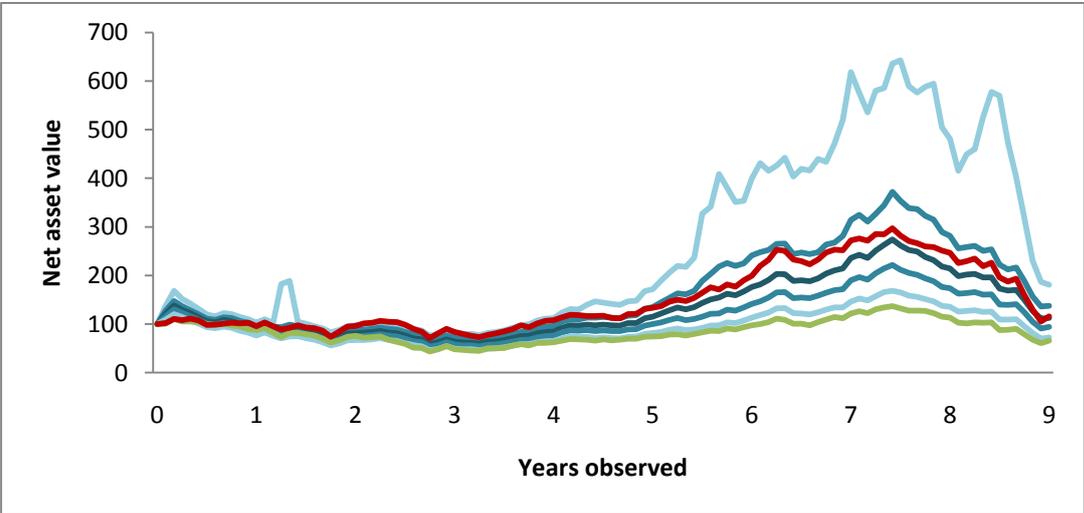


This observation led me to questioning the construction of the random portfolios. The true opportunity set of a manager would be every portfolio that a manager could have held. If you were able to observe the entire set you would also see within it the one portfolio that the manager had invested in. Obviously a Monte Carlo simulation is only a sample from the

real set. But a thousand random draws should be very close to the real distribution. Had they been drawn from the true opportunity set it would be highly unlikely that the 90% shown in figure 1 would all be above the fund average.

This in turn led me to a study of the stock data. Following the categorization found at Morningstar (2004) I divided my artificial stock market into large cap, mid cap and small cap stocks. 15 of the stocks were large cap, 26 were mid cap and 190 were small cap. Obviously randomly drawing stocks without any link between capitalization and portfolio weights had led to random portfolios with a high share of small cap stocks. I took a look at the average annual returns of these three stock types from my market. The large cap segment had an average return of -11.4%; the mid cap had an average of -3.2% and the small cap an average of 2.9%. The high concentration of small cap stocks combined with the relatively high return of this group could explain why the random portfolios outperformed my real fund sample. As can be seen from figure 2, the fit against the small cap index is better than that against the normal portfolio index.

Figure 2: Randomly weighted portfolio quantiles, 5%, 25%, 50%, 75%, 95% (in blue), the Swedish MSCI small cap index (in red) and the SIXPX (in green).



However, I do believe that these random portfolios are a part of the true opportunity set of real portfolios that the managers could have invested in. After all they are constructed from actual stocks that may well have been held by the managers. But because of the self imposed constraints that the managers were facing they would not hold these portfolios. Because of these constraints, the randomly weighted portfolios were of little interest to me

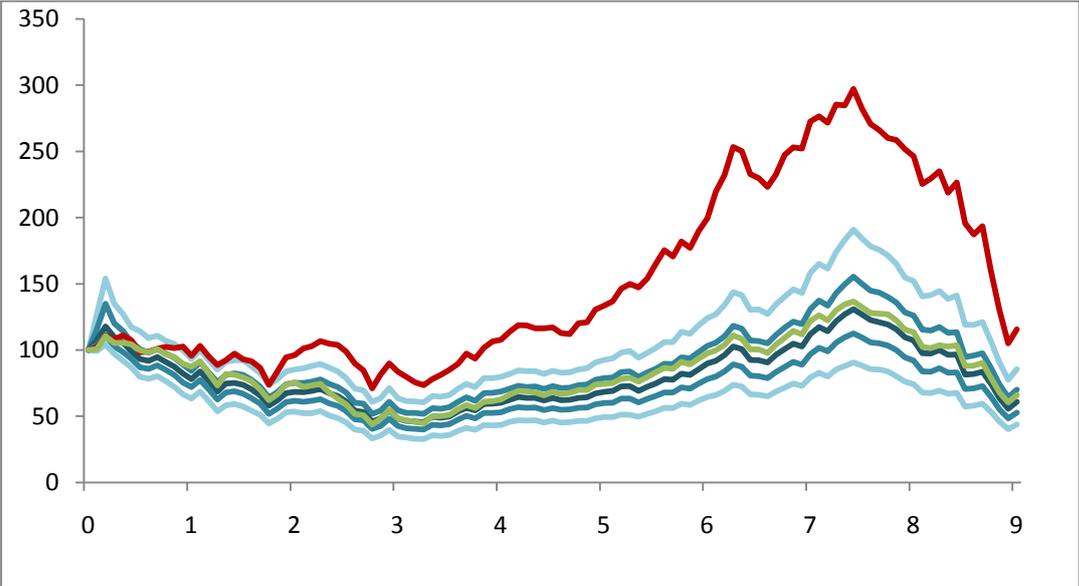
as a measure of comparison for the real managers. Obviously they were also very hard to beat in this period since the small cap segment did so well. Likewise they would have been easy to beat if the small cap was in decline. In a way this was similar to the index problem in Ippolito's (1989) study. It also reminded me of why Burns (2004) had advised against the use of indices.

Hence I did not use the randomly weighted portfolios anymore in my study of the actual fund managers.

4.1.2 Proportionally weighted portfolios

After having discarded the randomly weighted portfolios I had a look at the proportionally weighted random portfolios to see if they were a better opportunity set. Fortunately, as figure 3 shows, they had a much better fit against a normal portfolio index than the randomly weighted portfolios had. It should be noted, however, that they seem to be doing slightly worse than the SIXPX index. The fact that they had a much better fit was not so surprising since they had been constructed in a way that was much more similar to that of the real funds in the sample. The proportionally weighted portfolios are what was used as a measurement for the real managers in the following tests.

Figure 3: Proportionally weighted portfolio quantiles, 5%, 25%, 50%, 75%, 95% (in blue), the MSCI small cap index (in red) and the SIXPX (in green).



4.2 Constructing an artificial benchmark

As a first step in testing the null hypothesis an artificial benchmark was created. This benchmark was made from the average of the series of proportionally weighted random portfolios. Once the benchmark had been built, each fund had its information ratio calculated against it. First I calculated the ratio for the entire period, then for each of the three sub periods. After this, p-values could be calculated from the t-statistic mentioned earlier, using the fact that the degrees of freedom equalled the number of observations minus one (Truman 2003).

Using the random portfolios like this was not the best way of using them, as they contained much more information than could be fitted into a benchmark. Still I found it interesting to run this type of test and have a look at the information ratios resulting from it.

The results from the test are presented in Appendix, table 1. The average information ratio for the full period was 0.07. An information ratio of 0.07 is very low, but being positive it did suggest that manager skill might exist in my sample. When I studied the corresponding p-values I found only one manager with a positively significant result at a 5% level. This was not more than what could be explained by mere chance.

Next I did the same test, this time using the data including management fees. The results are shown in Appendix, table 2. This test showed an average information ratio of 0.21, which was a decent result. There was, however, still only one fund with a statistically significantly positive value. Again this could easily be explained by chance or in other words by luck. The results from the three individual sub periods were not higher. Only in one of the three sub periods did any fund at all get a significantly positive ratio and in that period it was still only one fund that managed this. The same was true even when adjustment had been made for management fees.

Consequently none of the results from these tests against the benchmark gave me any reason to reject the null hypothesis.

4.3 Opportunity groups

In my second test I used the random portfolios to create something very similar to the peer groups often used in performance evaluation. Naturally these peer groups differ from traditional peer groups in that they were not constructed from the real peers but from the random portfolios. The risk-adjusted performance index of the random portfolios was used

4.4 Combined p-values

Finally the time had come to try the real managers against the entire set of random portfolios. This was done using a method for combining p-values from different periods that had been proposed by Burns (2004). Because of the problem with negative information ratios I had to consider other measurements. In the end I decided to compare the unadjusted monthly returns from the real funds against those of the random portfolios. The reasoning behind this was as follows. First I had compared the average volatility of the funds to that of the random portfolios. The real funds had a volatility of 23% while the random portfolios had only 22.2% volatility. I reasoned that as the volatilities were fairly similar, the fund returns could be used as a performance measure. Furthermore, as the random portfolios actually had a lower volatility than the real funds had, this would only be a concern if evidence was found against the null hypothesis. For the object of proving the null hypothesis true this was not a problem.

The monthly returns of each fund were compared to those of every random portfolio yielding an individual series of monthly p-values for each fund. After this, these monthly p-values were combined into one single p-value for each fund, through the use of Stouffer's method for combining independent p-values as described in Burns (2004).

The results can be seen in Appendix, table 3. None of the funds had a positively significant combined p-value, while three funds had negatively significant p-values. This was at a 5% significance level for the entire distribution so the expected number of negatively significant observations had been 2.5%. In other words I had expected to find around 0.625 funds with significantly negative values. Three managers with significantly negative values at this level either implied that the managers had negative skill, or that their costs were higher than their gains.

I ran the same test one more time in order to find out which of the two explanations was the more likely. This time I used the data including management fees. The results from this test are presented in Appendix, table 4. These results were quite different. No managers with significantly negative values were found; instead, one manager with a significantly positive value was identified. Therefore, I was ready to accept that the negative values in the former test had been caused not by negative skill, but by high costs.

My conclusion after running this test was the same as before: Active managers did not possess superior stock selecting abilities or timing.

4.5 Picking a winner

As the tests had convinced me that the managers as a group had no superior skill, I now turned my attention to the individual managers to see if any of them showed any persistent results. Naturally, some managers had done better than others, but I still wondered if this was due to luck or actual skill on behalf of these managers. I wanted to test if there were any signs of persistence in their performance in my sample data. In order to do this I made an individual ranking of the managers for each of the three sub periods, based on their information ratios when compared to the artificial benchmark.

The findings are shown in Appendix, table 5 and are not very encouraging. If you had invested in the top three performers of period one hoping for similar results in the second period you would have been highly disappointed in your choice, as these funds ended up at positions 5, 23 and 25 in the second period. Someone who had invested in the top three performers from period two would have had slightly better luck, as they ended up at spots 2, 13 and 19 in the third period.

Finally, using the rankings from the different periods, the Spearman rank correlation coefficient was calculated between the adjacent periods (Zar 1972). The correlation between period one and two was 0.09 or in other words very close to zero correlation. The hypothesis of positive correlation is rejected even at a 50% significance level for this test. The correlation between period two and three was 0.19 which is a slightly stronger than the first result, but still far from significant and again positive correlation cannot be statistically proven, not even at a 20% significance level. Like with the earlier tests, the results can easily be explained by chance.

4.6 Is luck all you need?

My final test was a test of luck slightly inspired by Malkiel. But rather than running a coin flipping simulation I used the random portfolios to form the test for luck. In this test no real fund managers were involved at all; instead the participants were the 1000 proportionally weighted random portfolios. As these had been created with no utility function or any other optimization process they could be viewed as unskilled managers. These 1000 unskilled managers were then compared to the artificial benchmark created earlier from their investment universe. But first hypothetical yearly management fees of 2% per year were

subtracted from their NAV-series.⁶ These new series were compared to the artificial benchmark.

I had suspected luck to be a large factor in mutual fund performance, but the results from the test were still rather astonishing. After three years, 34.1% of the unskilled managers had managed to beat their market index with the help of nothing but luck. After five years 25.4% of the managers were still in the game. Finally, after the full nine year period there were still 17.2% who were lucky enough to beat the benchmark. These figures were calculated with a fairly high management fee and might very well be representative for real managers. If that is the case, then luck is probably all that is needed.

⁶ The average management fee of the real funds was 1.3%.

5. Concluding remarks

In this thesis I have studied the performance of 25 actively managed Swedish mutual funds. Due to the unpredictability in the stock market it can be very challenging to evaluate fund performance accurately. This makes it very hard to state with certainty whether the past performance of a fund has been a result of manager skill or of manager luck.

In order to completely assess the decisions of a fund manager, we would need to identify all the options that were available to him or her. We would need to compare the chosen investment to all the investments that were not chosen. Unfortunately the number of possible investment options is at many times close to infinite.

The way I tried to solve this problem was by generating a large set of random portfolios. These random portfolios were created from a set of stocks I believed to be a good representation of the managers' true investment universe. When I constructed these random portfolios I tried to mirror as closely as I could the investment style of the managers. I also tried to the best of my abilities to conform to any constraints that the managers were facing. One crucial difference existed between me and the managers: I created my portfolios at random, without any information as help.

In my comparison between the real funds and the randomly created portfolios I did not find any evidence that could attribute past fund performance to skill rather than to luck. If these managers had superior stock selecting abilities or timing it did not show in this study. Neither did I identify any persistence in fund performance. A fund might be one of the top three performers in one period, only to end up as the worst performer in the next period.

These results are in accordance with much of the earlier literature on the topic. The semi strong version of the efficient market hypothesis seems to hold true in the Swedish fund market. This however does not necessarily mean that all of the investors act rationally. After all, a majority of them are still investing in actively managed funds even when advised not to. To me this looks more like speculating or betting on the winner than it looks like saving money for the future. If gambling is what the investors are looking for, I would advise them to go to a casino. If they are saving for the future, I would tell them to buy and hold, diversify or invest in an index fund.

References

Benninga, S. (2008) 3rd edn. *Financial modelling*. Cambridge: MIT Press

Burns, P. (2004). *Performance Measurement via Random Portfolios* [online]. Available from November 10, 2009, <<http://www.burns-stat.com/pages/working.htm>> [10 November 2009]

Burns, P. (2009). *Random portfolios in finance* [online]. Available from <http://www.burns-stat.com/pages/Finance/random_portfolios.html> [15 January 2010]

Carhart, M. (1997). 'On persistence in mutual fund performance.' *Journal of Finance* 52, (1) 57-82

Elton, E., Gruber, M., Brown, S., Goetzmann, W. (2007) 7th edn. *Modern portfolio theory and investment analysis*. New York: John Wiley & Sons

Elton, E., Gruber, M., Das, S., & Hlavka, M. (1993) 'Efficiency with costly information: A reinterpretation of evidence from managed portfolios.' *Review of financial studies* 6, (2) 1-22.

Fama, E. (1970) 'Efficient capital markets: A review of theory and empirical work.' *Journal of finance* 25, (2) 383-417

Fama, E. (1991) 'Efficient capital markets: II.' *Journal of finance* 46, (5) 1575-1618

Fondbolagens förening (c. 2010) *Marknadsindex* [online]. Available from <<http://www.fondbolagen.se/StatistikStudier/Index/Index/Marknadsindex.aspx>> [7 January 2010]

- Fox, J. (2002) 'Is the market rational? – No, say the experts. But neither are you – so don't go thinking you can outsmart it.' *Fortune Magazine* 9 December: 59-64
- Ippolito, R. (1989) 'Efficiency with costly information: A study of mutual fund performance, 1965-1984.' *Quarterly Journal of Economics* 104, (1) 1-24
- Jensen, M. (1968) 'The performance of mutual funds in the period 1945-1964.' *Journal of finance* 23, (2) 389-416
- Kahneman, D., Tversky, A. (1979) 'Prospect theory: An analysis of decision under risk.' *Econometrica* 47, (2) 263-292
- Malkiel, B. (1985) 4th edn. *A random walk down Wall Street*. New York: Norton
- Malkiel, B. (1995) 'Returns from investing in equity mutual funds 1971 to 1991.' *Journal of Finance* 50, (2) 549-572
- Malkiel, B. (2003) 'The efficient market hypothesis and its critics.' *Journal of economic perspectives* 17, (1) 59-82
- Malkiel, B. (2005) 'Reflections on the efficient market hypothesis: 30 years later.' *Financial review* 1, (40) 1-10
- Morningstar (2004) *Fact sheet: The Morningstar trade box* [online]. Available from <<http://morningstar.ekuriren.se/Static/MorningstarStyleBoxFactSheet2004.pdf>> 30 December 2009
- Morningstar (2009) *Sök fond: Alla fonder* [online]. Available from <<http://www.morningstar.se/Funds/Quickrank.aspx>> [27 November 2009]
- Riksbanken (2010) *Statsskuldväxlar* [online]. Available from <<http://www.riksbank.se/templates/stat.aspx?id=16739>> [10 January 2010]

Scholz, H. (2007) *Journal of Asset Management* 7, (5) 347-358

Sharpe, W. (1994) 'The Sharpe ratio.' *Journal of Portfolio Management* 21, (1) 49-59

Statman, M. (1987) 'How many stocks make a diversified portfolio?' *Journal of financial and quantitative analysis* 22, (3) 353-363

Surz, R. (1996) 'Portfolio opportunity distributions: A solution to the problems with benchmarks and peer groups.' *Journal of Performance Measurement* 1, (2) 24-31

Thaler, R. (1980) 'Toward a positive theory of consumer choice.' *Journal of Economic Behaviour and Organization* 1, (1) 39-60

Truman, C. (2003) *Inside the Information ratio* [online]. Available from
<<http://masecofinancial.com/pubs/Inside%20the%20Information%20Ratio.pdf>> [7
January 2010]

Zar, J. (1972) 'Significance testing of the Spearman rank correlation coefficient.' *Journal of the American statistical institution* 67, (339) 578-581

Appendix

TABLE 1

Information ratios, t-statistics and p-values for individual mutual funds, when compared to a benchmark calculated from proportional weighted random portfolios

Fund	IR	t-statistic	P-value	Fund	IR	t-statistic	P-value
AMF Aktiefond Sverige	0,68	2,04	4,4%	Folksam Aktiefond Sverige	0,01	0,04	97,1%
2000-2003	1,25	2,17	3,7%	2000-2003	0,03	0,05	96,2%
2003-2006	0,27	0,46	64,8%	2003-2006	0,01	0,02	98,2%
2006-2009	0,25	0,44	66,4%	2006-2009	-0,01	-0,02	98,5%
Aktie-Ansvar Sverige	0,30	0,91	36,7%	Handelsbanken Bofond	-0,05	-0,15	87,8%
2000-2003	0,77	1,33	19,2%	2000-2003	-0,16	-0,28	77,8%
2003-2006	-0,34	-0,58	56,5%	2003-2006	-0,11	-0,19	85,3%
2006-2009	0,09	0,16	87,7%	2006-2009	0,22	0,38	70,6%
Banco Etisk Sverige	-0,28	-0,84	40,5%	Handelsbanken Sverigefond	-0,08	-0,24	80,8%
2000-2003	-0,45	-0,78	43,8%	2000-2003	-0,24	-0,42	67,7%
2003-2006	-0,04	-0,06	95,0%	2003-2006	-0,11	-0,18	85,5%
2006-2009	-0,20	-0,35	72,7%	2006-2009	0,25	0,43	67,3%
Banco Etisk Sverige Special	-0,19	-0,58	56,3%	HQ Sverige	0,44	1,31	19,2%
2000-2003	-0,35	-0,61	54,6%	2000-2003	1,00	1,73	9,3%
2003-2006	0,02	0,03	97,8%	2003-2006	-0,71	-1,23	22,9%
2006-2009	-0,10	-0,18	85,8%	2006-2009	0,73	1,27	21,2%
Banco Hjälp	-0,47	-1,42	15,9%	Länsförsäkringar Sverigefond	0,03	0,08	93,7%
2000-2003	-0,70	-1,22	23,1%	2000-2003	-0,07	-0,12	90,5%
2003-2006	-0,35	-0,60	55,3%	2003-2006	-0,02	-0,04	97,2%
2006-2009	-0,26	-0,45	65,7%	2006-2009	0,25	0,43	67,3%
Banco Svensk Miljö	0,18	0,55	58,1%	Nordea Etiskt Urval	0,14	0,41	68,4%
2000-2003	0,15	0,26	79,4%	2000-2003	0,25	0,43	67,3%
2003-2006	0,28	0,48	63,4%	2003-2006	-0,20	-0,34	73,6%
2006-2009	0,20	0,35	72,5%	2006-2009	0,21	0,37	71,2%
Banco Sverige	-0,48	-1,44	15,2%	Nordea Sverigefonden	-0,09	-0,28	77,6%
2000-2003	-0,55	-0,95	35,1%	2000-2003	-0,31	-0,53	59,8%
2003-2006	-0,25	-0,44	66,2%	2003-2006	-0,07	-0,13	89,9%
2006-2009	-0,61	-1,06	29,7%	2006-2009	0,24	0,42	67,7%
Carlson Sverigefond	0,12	0,37	70,9%	Robur Ethica Miljö Sverige	0,05	0,15	87,7%
2000-2003	0,12	0,21	83,3%	2000-2003	0,18	0,32	75,4%
2003-2006	0,08	0,13	89,4%	2003-2006	-0,24	-0,42	67,7%
2006-2009	0,18	0,31	75,6%	2006-2009	0,08	0,14	88,9%
Catella Reavinstfond	0,30	0,89	37,6%	Robur Sverigefond	0,11	0,33	74,3%
2000-2003	0,21	0,37	71,3%	2000-2003	-0,04	-0,07	94,4%
2003-2006	0,87	1,50	14,3%	2003-2006	0,43	0,75	45,7%
2006-2009	0,05	0,09	92,7%	2006-2009	0,15	0,26	80,0%
Danske Invest, Sverige	0,21	0,62	53,7%	Skandia Aktiefond Sverige	0,14	0,41	68,5%
2000-2003	0,49	0,85	40,1%	2000-2003	0,19	0,33	74,4%
2003-2006	-0,11	-0,20	84,5%	2003-2006	0,06	0,11	91,5%
2006-2009	0,04	0,08	94,1%	2006-2009	0,12	0,21	83,4%
Eldsäl Sverigefond	0,16	0,48	63,5%	SPP Aktiefond Sverige	0,21	0,64	52,7%
2000-2003	-0,16	-0,27	79,0%	2000-2003	0,29	0,50	62,0%
2003-2006	0,58	1,00	32,5%	2003-2006	0,02	0,04	96,9%
2006-2009	0,44	0,76	45,3%	2006-2009	0,27	0,47	64,0%
Folksam LO Sverige	0,13	0,39	69,9%	Öhman Fonder Sverige	0,00	-0,01	99,3%
2000-2003	0,18	0,31	75,9%	2000-2003	0,07	0,12	90,6%
2003-2006	0,15	0,25	80,1%	2003-2006	-0,29	-0,50	62,1%
2006-2009	0,06	0,10	92,0%	2006-2009	0,11	0,20	84,5%
Folksam LO Västfonden	0,19	0,56	57,9%				
2000-2003	0,21	0,36	72,3%				
2003-2006	0,18	0,32	75,1%				
2006-2009	0,18	0,31	76,0%				

TABLE 2

Information ratios, t-statistics and p-values for individual mutual funds with management fees added back, when compared to a benchmark calculated from proportional weighted random portfolios

Fund	IR	t-statistic	p-value	Fund	IR	t-statistic	p-value
AMF Aktiefond Sverige	0.72	2.17	3.2%	Folksam Aktiefond Sverige	0.09	0.26	79.3%
2000-2003	1.28	2.23	3.3%	2000-2003	0.08	0.14	88.7%
2003-2006	0.34	0.58	56.3%	2003-2006	0.13	0.23	82.2%
2006-2009	0.30	0.52	60.5%	2006-2009	0.07	0.13	90.0%
Aktie-Ansvar Sverige	0.48	1.43	15.6%	Handelsbanken Bofond	0.20	0.60	54.7%
2000-2003	0.90	1.55	12.9%	2000-2003	0.00	0.01	99.4%
2003-2006	-0.04	-0.08	93.8%	2003-2006	0.32	0.55	58.3%
2006-2009	0.28	0.49	62.9%	2006-2009	0.58	1.00	32.2%
Banco Etisk Sverige	-0.11	-0.34	73.4%	Handelsbanken Sverigefond	0.07	0.21	83.7%
2000-2003	-0.34	-0.59	55.7%	2000-2003	-0.14	-0.24	80.9%
2003-2006	0.25	0.43	66.9%	2003-2006	0.12	0.21	83.3%
2006-2009	0.02	0.04	97.0%	2006-2009	0.45	0.78	43.9%
Banco Etisk Sverige Special	-0.09	-0.27	78.5%	HQ Sverige	0.61	1.82	7.2%
2000-2003	-0.28	-0.49	62.7%	2000-2003	1.13	1.96	5.8%
2003-2006	0.18	0.32	75.2%	2003-2006	-0.49	-0.85	40.1%
2006-2009	0.04	0.06	95.1%	2006-2009	0.92	1.60	11.8%
Banco Hjälp	-0.29	-0.86	39.0%	Länsförsäkringar Sverigefond	0.16	0.47	63.8%
2000-2003	-0.58	-1.00	32.4%	2000-2003	0.02	0.04	97.0%
2003-2006	-0.02	-0.04	97.0%	2003-2006	0.18	0.31	76.2%
2006-2009	-0.02	-0.04	97.1%	2006-2009	0.41	0.72	47.9%
Banco Svensk Miljö	0.38	1.15	25.2%	Nordea Etiskt Urval	0.29	0.86	39.1%
2000-2003	0.29	0.50	61.9%	2000-2003	0.35	0.60	55.2%
2003-2006	0.60	1.03	30.9%	2003-2006	0.07	0.13	90.0%
2006-2009	0.46	0.79	43.6%	2006-2009	0.42	0.73	47.1%
Banco Sverige	-0.32	-0.95	34.7%	Nordea Sverigefonden	0.04	0.12	90.2%
2000-2003	-0.42	-0.73	46.8%	2000-2003	-0.21	-0.37	71.3%
2003-2006	-0.02	-0.03	97.7%	2003-2006	0.18	0.31	75.7%
2006-2009	-0.42	-0.73	46.9%	2006-2009	0.41	0.71	48.3%
Carlson Sverigefond	0.25	0.76	45.0%	Robur Ethica Miljö Sverige	0.19	0.58	56.6%
2000-2003	0.21	0.37	71.4%	2000-2003	0.28	0.48	63.1%
2003-2006	0.29	0.51	61.5%	2003-2006	-0.03	-0.06	95.4%
2006-2009	0.33	0.57	57.3%	2006-2009	0.27	0.47	64.3%
Catella Reavinstfond	0.44	1.32	19.0%	Robur Sverigefond	0.26	0.77	44.2%
2000-2003	0.32	0.55	58.8%	2000-2003	0.06	0.11	91.6%
2003-2006	1.10	1.90	6.5%	2003-2006	0.68	1.17	24.9%
2006-2009	0.22	0.39	69.9%	2006-2009	0.33	0.58	56.8%
Danske Invest, Sverige	0.36	1.08	28.4%	Skandia Aktiefond Sverige	0.30	0.89	37.4%
2000-2003	0.60	1.04	30.3%	2000-2003	0.30	0.53	60.2%
2003-2006	0.11	0.20	84.4%	2003-2006	0.32	0.55	58.8%
2006-2009	0.22	0.37	71.0%	2006-2009	0.32	0.55	58.5%
Eldsjäl Sverigefond	0.33	1.00	32.1%	SPP Aktiefond Sverige	0.29	0.86	39.3%
2000-2003	-0.04	-0.06	95.1%	2000-2003	0.34	0.59	55.7%
2003-2006	0.86	1.49	14.4%	2003-2006	0.13	0.22	82.5%
2006-2009	0.66	1.14	26.1%	2006-2009	0.36	0.63	53.6%
Folksam LO Sverige	0.17	0.52	60.5%	Öhman Fonder Sverige	0.13	0.39	69.7%
2000-2003	0.21	0.36	71.8%	2000-2003	0.17	0.29	77.5%
2003-2006	0.22	0.37	71.1%	2003-2006	-0.09	-0.16	87.2%
2006-2009	0.11	0.18	85.4%	2006-2009	0.26	0.46	65.0%
Folksam LO Västfonden	0.23	0.69	49.1%				
2000-2003	0.24	0.41	68.2%				
2003-2006	0.26	0.45	65.9%				
2006-2009	0.23	0.39	69.6%				

TABLE 3

Combined p-values of individual mutual funds when compared to proportionally weighted random portfolios

Fund	left tail (negative)	right tail (positive)
AMF Aktiefond Sverige	96.5%	3.5%
Aktie-Ansvar Sverige	84.1%	15.9%
Banco Etisk Sverige	2.4%	97.6%
Banco Etisk Sverige Special	3.4%	96.6%
Banco Hjälp	0.4%	99.6%
Banco Svensk Miljö	43.5%	56.5%
Banco Sverige	0.6%	99.4%
Carlson Sverigefond	39.7%	60.3%
Catella Reavinstfond	58.6%	41.4%
Danske Invest, Sverige	70.0%	30.0%
Eldsäl Sverigefond	53.1%	46.9%
Folksam LO Sverige	43.1%	56.9%
Folksam LO Västfonden	56.6%	43.4%
Folksams Aktiefond Sverige	29.5%	70.5%
Handelsbanken Bofond	18.9%	81.1%
Handelsbanken Sverigefond	16.0%	84.0%
HQ Sverige	79.4%	20.6%
Länsförsäkringar Sverigefond	20.5%	79.5%
Nordea Etiskt Urval	26.2%	73.8%
Nordea Sverigefonden	26.2%	73.8%
Robur Ethica Miljö Sverige	30.9%	69.1%
Robur Sverigefond	58.3%	41.7%
Skandia Aktiefond Sverige	47.9%	52.1%
SPP Aktiefond Sverige	53.2%	46.8%
Öhman Fonder Sverige	20.3%	79.7%

TABLE 4

Combined p-values of individual mutual funds with management fees added back when compared to proportionally weighted random portfolios

Fund	left tail (negative)	right tail (positive)
AMF Aktiefond Sverige	97.7%	2.3%
Aktie-Ansvar Sverige	96.0%	4.0%
Banco Etisk Sverige	13.3%	86.7%
Banco Etisk Sverige Special	9.4%	90.6%
Banco Hjälp	4.1%	95.9%
Banco Svensk Miljö	76.7%	23.3%
Banco Sverige	4.5%	95.5%
Carlson Sverigefond	64.5%	35.5%
Catella Reavinstfond	84.5%	15.5%
Danske Invest, Sverige	88.9%	11.1%
Eldsäl Sverigefond	81.5%	18.5%
Folksam LO Sverige	52.8%	47.2%
Folksam LO Västfonden	65.3%	34.7%
Folksams Aktiefond Sverige	44.8%	55.2%
Handelsbanken Bofond	68.8%	31.2%
Handelsbanken Sverigefond	43.7%	56.3%
HQ Sverige	93.9%	6.1%
Länsförsäkringar Sverigefond	43.2%	56.8%
Nordea Etiskt Urval	57.1%	42.9%
Nordea Sverigefonden	55.1%	44.9%
Robur Ethica Miljö Sverige	58.5%	41.5%
Robur Sverigefond	82.8%	17.2%
Skandia Aktiefond Sverige	74.3%	25.7%
SPP Aktiefond Sverige	68.7%	31.3%
Öhman Fonder Sverige	40.3%	59.7%

TABLE 5

Individual ranking based on information ratios when compared to a benchmark calculated from proportional weighted random portfolios

Fund	2000- 2003	2003- 2006	2006- 2009
AMF Aktiefond Sverige	1	5	4
HQ Sverige	2	25	1
Aktie-Ansvar Sverige	3	23	16
Danske Invest, Sverige	4	18	20
SPP Aktiefond Sverige	5	10	3
Nordea Etiskt Urval	6	19	9
Catella Reavinstfond	7	1	19
Folksam LO Västfonden	8	6	12
Skandia Aktiefond Sverige	9	9	14
Robur Ethica Miljö Sverige	10	20	17
Folksam LO Sverige	11	7	18
Banco Svensk Miljö	12	4	10
Carlson Sverigefond	13	8	11
Öhman Fonder Sverige	14	22	15
Folksams Aktiefond Sverige	15	12	21
Robur Sverigefond	16	3	13
Länsförsäkringar Sverigefond	17	13	5
Eldsäl Sverigefond	18	2	2
Handelsbanken Bofond	19	17	8
Handelsbanken Sverigefond	20	16	6
Nordea Sverigefonden	21	15	7
Banco Etisk Sverige Special	22	11	22
Banco Etisk Sverige	23	14	23
Banco Sverige	24	21	25
Banco Hjälp	25	24	24