

Asset Allocation, Security Selection And Market Timing in Mutual Funds

Master Thesis in Economic Analysis (ECO)

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This thesis was written as a part of the Master of Science in Economics and Business Administration at NHH. Neither the institution, the advisor, nor the sensors are - through the approval of this thesis - responsible for neither the theories and methods used, nor results and conclusions drawn in this work.

I. PREFACE

As the title indicates, this thesis is about asset allocation, security selection and market timing in mutual funds. This is a topic that should be of interest for most people that let mutual funds handle their personal wealth or pension liabilities. Natural questions to ask in this matter are “What asset classes is my wealth/pension exposed to?” and “How is the performance of my manager?” This thesis will enable investors to answer such questions, and more.

When I was on exchange at Johnson School at Cornell University, I was introduced to these exciting topics in a course called “Investments” taught by Professor G. Saar. During this course I was also introduced to many interesting academic papers. Among these, were two papers which have an important part in this thesis; namely “Asset Allocation: Management Style and Performance Measurement” by Nobel laureate W. Sharpe (1992) and “Determinants of Portfolio Performance” by Brinson, Hood, and Beebower (1986). Both these papers combine mathematics and econometrics into elegant and pedagogical models. Basically, this thesis combines the insight from these papers to answer a set of questions that are relevant for people investing in mutual funds.

The process of writing this thesis has been interesting and challenging at the same time. I have had the possibility to be both creative and to use accumulated knowledge. Most importantly, the process of writing this thesis has enabled me to learn much more about topics that I find very interesting. Having taken courses such as “Financial Theory”, “Econometric Techniques”, “Times Series Analysis and Prediction” and “Empirical Analysis of Financial and Commodity Markets” has been vital in order to write this thesis.

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III. ABSTRACT

CHAPTER 1: Estimating Determinants of a Mutual Fund's Risk and Managerial Performance

In this chapter, we construct a framework that can be used by investors to independently estimate a mutual fund's actual and policy weights in a set of predefined asset classes, and to estimate a mutual fund's security selection and market timing. Our framework has its foundation in a paper by Brinson, Hood and Beebower (1986). By generalizing the ideas in their paper, we see that we can measure a fund's security selection and market timing only if we have the actual and policy weights. We argue that weights that reflect the fund's short-term and long-term behavior are good estimates of a fund's actual and policy weights respectively. In this matter, we can get estimates of the actual and policy weights by using Return Based Style Analysis (Sharp, 1992) in two steps. These estimates can in turn be used to estimate the fund's security selection and market timing.

CHAPTER 2: An Empirical Study of Norwegian Mutual Fund Managers

In this chapter, we use the framework developed in chapter 1 to answer 3 important questions related to Norwegian mutual fund managers: 1) How much of the total variation in mutual fund return is explained by asset allocation, security selection and market timing respectively? 2) Is the average managerial performance positive? 3) Ceteris paribus, does a change in a mutual fund's management cause a change in managerial performance? We find that a fund's respective asset allocation, security selection and market timing explain 90.6%, 4.5% and 4.9% of the variation over time. Moreover, we find that the mutual funds are good in picking stocks, but loose by timing the market. In sum, the managerial performance is not significantly different from 0. We also find that when poor performing managers are replaced, excess return increases significantly. The opposite result holds when the very best managers are replaced.

JEL Classification: C32; C61; G20; G23

Keywords: Asset Allocation; Security Selection; Market Timing; Return Based Style Analysis

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*“Next, where the Sirens dwells, you plough the seas;
Their song is death, and makes destruction please.
Unblest the man, whom music wins to stay
Nigh the cursed shore and listen to the lay.
No more that wretch shall view the joys of life
His blooming offspring, or his beauteous wife!
In verdant meads they sport; and wide around
Lie human bones that whiten all the ground:
The ground polluted floats with human gore,
And human carnage taints the dreadful shore
Fly swift the dangerous coast: let every ear
Be stopp’d against the song! ‘tis death to hear!
Firm to the mast with chains thyself be bound,
Nor trust thy virtue to the enchanting sound.
If, mad with transport, freedom thou demand,
Be every fetter strain’d, and added band to band.”*

The Odyssey XII, by Homer

INTRODUCTION

Asset allocation, Security Selection and Market Timing in Mutual Funds

In the epic poem *Odyssey*, Homer writes that Odysseus wanted to reassert his place as the rightful king of Ithaca. In this matter, he had to sail the perilous route from Circe’s Island to Ithaca. Equivalently, mutual funds and their managers have to guide themselves through a sea of risky investments in order to reach their goals of becoming the kings of the financial industry.

Circe advised Odysseus to sail a specific route in order to get to Ithaca. Hence, Odysseus had a pre-defined route with some expected dangers, much like mutual funds have a pre-defined *asset allocation* with a given level of expected risk. Asset allocation refers to the long-term decision regarding the proportions of total assets that an investor chooses to place in particular classes of investments (Swensen, 2005). We call these long-term proportions *policy weights*. These weights are often based on an underlying *investment philosophy*, which is a coherent way of thinking about how financial markets work.

New information and events happening along the pre-defined route made it tempting for Odysseys to deviate from Circe’s advice. One such situation occurred when Odysseys had to pass the Sirens. The sirens were creatures that sung so beautiful that sailors were lured to sail into a deathly shore. Odysseus was curious as to what the Sirens sounded like. Therefore, on

Circe's advice, he had all his sailors plug their ears with beeswax and tie him to the mast. He ordered his men to leave him tied to the mast no matter how much he would beg them to untie him. When Odysseus heard the sirens' beautiful song, he ordered the sailors to untie him, but they bound him just tighter. When the ship had passed the Sirens out of earshot, Odysseus signaled with his frowns to be released. Although Odysseus found it tempting to deviate from his pre-defined route as he passed the Sirens, this would have ended his journey. Hence, he well in listening to Circe's advice and stick to the pre-defined route.

Just as Odysseus had the possibility to deviate from his pre-defined route, your mutual fund manager can choose to deviate from the policy weights by strategic under- or overweighting the asset classes. We call this *market timing*. Market timers hope to underweight prospectively poorly performing asset classes and overweight prospectively strongly performing asset classes to enhance portfolio returns (Swensen, 2005). Due to market timing, the short-term risk will deviate from normal levels, and the short-term proportions placed in particular classes of investments will deviate from the policy weights. We call the mutual fund's proportions placed in particular classes of investments in the beginning of the current period (hence short-term) for *actual weights*. These weights constitute the mutual fund's *current allocation*.

Economists have for long questioned what a mutual fund's optimal portfolio choice should be. Mossin (1968), Merton (1969, 1971) and Samuelson (1969) (hereafter MMS) were first to find an answer. To exemplify MMS' findings, say we have a mutual fund that wants to maximize its expected utility of assets under management (final wealth) with respect to its allocation between equity and bonds. MMS show that the multiperiod problem is degenerated into several one-period problems under the following assumptions (Aase, 2009):

- i) The returns of the asset classes are independently and identically distributed with jointly normally distributions (i.e., returns of equity and bonds have constant expectation and standard deviation)
- ii) The mutual fund has a additively separable constant relative risk-aversion (i.e., risk aversion is independent of the assets under management)
- iii) The mutual fund has no non-tradable assets (i.e., only investment income is considered)

iv) Financial markets (i.e., stock and bond market) are frictionless and complete¹

Under these assumptions, the solution to the problem satisfying the assumptions can be shown to give a constant allocation between equity and bonds, which is independent of both investment horizon and the mutual fund's assets under management. Presumably, this constant allocation is the same as the mutual fund's policy weights for equity and bonds. This implies that when the stock market boosts, it is optimal to sell equity and buy bonds, whereas when the stock market falls, the fund should sell bonds and buy equity. This argument can be generalized to n asset classes, making it optimal to stick to the policy weights which are found by solving MMS' problem. Of course, for practical purposes, mutual funds just pick some subjective policy weights that they feel are according to their desired level of risk.

Based on the above arguments, the discretionary policy of market timing is not optimal. Just like Circe advised Odysseus to bind himself to the mast and stick to his pre-defined route, the economists advise mutual fund managers to stick to their predefined policy-weights. In effect, this is an argument for rules rather than discretion; mutual funds that do this have policy weights that are equal to their actual weights.

Although economists have long advised investors not to time the market, buying equity in a bear market and selling equity in a bull market is contrary to human nature. Humans go in crowds and engage in counterproductive performance by buying yesterday's winners and selling yesterday's losers. Interestingly, the most frequent variant of market timing comes not in the form of explicit bets for or against asset classes, but in the form of a passive drift away from target allocations (Swensen, 2005). If investors fail to counter market moves by rebalancing their portfolio, the allocation inevitably moves away from the policy weights. A simple buy and hold portfolio is an example of a strategy that passively drifts away from the policy weights in the long run.

Based on MMS's arguments, we can expect that successful mutual funds are able to act in a contrarian way, and that they rebalance their portfolios as often as possible. However, if MMS's assumptions are too strict, market timing might be valuable. For example, if a mutual

¹ A complete market is a system of market in which every agent (here: mutual fund) is able to exchange every good (here: bonds and equity), either directly or indirectly, with every other agent (Flood, 1991)

fund finds that past returns of a specific asset class can be used to predict future returns, this is clearly something they should take advantage of by timing the market.

By improving the sailing along the pre-defined route, Odysseus could get to Ithaca quicker. Equivalently in the capital markets, your mutual fund manager will try to pick the stocks that boost the mutual fund's return. This tool is called *security selection*, and is the active selection of investments within an asset class (Brinson, Hood and Beebower, 1986). The amount of security selection that is generated by a mutual fund is dependent on the market's efficiency.

Roberts (1967) and Fama (1970) define three levels of market efficiency: weak form, semi-strong form, and strong form market efficiency. The *weak form market efficiency* claims that stock prices reflect all past public information and that it is not possible to earn positive security selection based on historical information. *Semi-strong form market efficiency* says that stock prices reflect all publicly available information. Hence, new public information will instantly be absorbed into the price. *Strong form market efficiency* claims that all public and private information are reflected in the stock price; this implies that inside information is baked into the price. Beating the market by security selection and not luck is dependent on information or skills. This implies that a market with successful active management cannot be efficient in the semi-strong form.

A *benchmark* is the standard in which the mutual fund's return is evaluated against. A *passive mutual fund* tries to track a given benchmark whereas an *active mutual fund* attempts to generate return in excess of the benchmark. Sharpe (1991) argues that over any specified time period, the market return must equal a weighted average of the return on the passive and active segments of the market. Since each passive manager obtains exactly the market return, before costs, it follows that the return on the average actively managed dollar must equal the market return. Since the cost of the actively managed dollar is larger than the passively managed dollar, it implies that after cost, the return on the average actively managed dollar will be less than the return on the average passively managed dollar. This can have two implications: 1) the average active return of mutual funds is negative after cost, or 2) active return is positive at the expense of investors outside the mutual funds. If mutual funds do indeed have skills or have information, they will be in the second category.

Problem Statements and Disposal

We have now discussed the 3 tools capital markets provide for mutual funds to employ in generating investment returns: asset allocation, security selection and market timing. Together these tools constitute the determinants of a mutual fund's return. The return associated to the asset allocation is the investor's responsibility and not the manager's, since the investor chooses to bet on that particular risk. Since it is the investor's job to find out whether a mutual fund suits their risk-tolerance, it is essential to have an overview of a funds' risk. A mutual fund's risk is a function of its investments; hence, the determinants of current (short-term) and normal (long-term) risk can be measured by the actual and policy weights respectively. The question is: how do we get access to these weights?

Most managers provide some form of information to their investors regarding what they currently invest in and what their asset allocation is. However, different managers interpret and define investments differently; thus, if one invests in many different mutual funds, it might be hard to see through what assets classes one's money is really exposed to and whether the bets offset each other. Moreover, the information from the mutual funds may be delayed and even false. In fact, DiBartolomeo and Witkowski (1997) and Brown and Goetzmann (1997) find that up to 40% of mutual funds are misclassified if self-reported investment objectives are compared to actual investments. Thus, moral hazard is a large problem.

Once an asset allocation has been made, it is up to the mutual fund's manager to enhance the fund's return through security selection and/or market timing. Thus we say that the determinants of managerial performance are security selection and market timing. In order for investors to be able to evaluate a manager's performance and to gain an understanding on whether it is worth paying management fees for active management, we need an overview of how much security selection and market timing the fund has been able to create historically. The sequential question is: does the mutual fund provide us with these figures?

Fortunately, most portfolio managers provide information to their investors regarding how much return they create in excess of some benchmark. However, few managers tell us how much is created by security selection and market timing respectively. Moreover, if the mutual fund uses a benchmark with less risk than the risk of their asset allocation, it is a tautology

that they manage to beat their benchmark on average, without utilizing security selection and market timing (provided that financial theory works).

With the above issues in mind, it would be useful for investors to have a framework that allows them to independently measure the determinants of a mutual fund's risk and managerial performance. Hence, in chapter 1, we aim to develop a framework that answers the following problem statements:

- *How can an investor estimate a mutual fund's actual and policy weights in a set of asset classes?*
- *How can an investor estimate a mutual fund's security selection and market timing?*

We will see that the two problem-questions are closely related, and the second problem statement cannot be answered without answering the first problem statement. In order to illustrate the framework that is used to discuss these problem statements, we will apply it on active Norwegian mutual funds that focus on the Norwegian equity market.

In Chapter 2 we use the framework developed in Chapter 1 to study three important questions related to Norwegian mutual fund managers:

- 1) *How much of the total variation in mutual fund return is explained by asset allocation, security selection and market timing respectively?*
- 2) *Is the average managerial performance positive?*
- 3) *Ceteris paribus, does a change in a mutual fund's management cause a change in managerial performance?*

The results of these problem statements are relevant in order to understand the importance of mutual funds and their managers.

In appendix A is a list of definitions of the terms that are frequently used in this thesis.

CHAPTER 1:

Estimating Determinants of a Mutual Fund's Risk and Managerial Performance

– A Two-Step Approach using Return Based Style Analysis

1.1. Introduction

A mutual fund's risk is a function of its investments. This implies that the determinants of a mutual fund's short- and long-term risk are measured by the fund's actual and policy weights respectively. Once an asset allocation has been made, it is the manager's task to enhance the fund's performance by security selection and/or market timing. This implies that the determinants of managerial performance are measured by the amount of security selection and market timing the fund utilizes. The purpose of this chapter is to develop a framework that can easily be used by investors to independently estimate a mutual fund's actual weights and policy weights in a set of asset classes, and to estimate a mutual fund's security selection and market timing.

In the classical paper "Determinants of Portfolio Performance" (1986), Brinson, Hood, and Beebower propose a framework that decomposes pension plan returns into benchmark return, market timing and security selection. We will see by generalizing this framework, we are able to get measures of a mutual fund's security selection and market timing. However, to get these figures, we have to know the fund's actual and policy weights of a set of predefined asset classes in advance. One method which can be used to find these weights has become known as "Portfolio Based Style Analysis". This is an approach in which the characteristics of a fund over a period of time are derived from the characteristics of the securities it contains at various points in time. Such a method requires the need of a database that contains the characteristics of each security in the investable universe of the fund being analyzed. Furthermore, it requires a record of the security holdings of each fund being analyzed

(Kaplan, 2003). Unfortunately, investors do not usually have the ability, time or money to build and update such databases.

In the paper entitled “Asset Allocation: Management Style and Performance Measurement”,² Nobel laureate W. F. Sharpe (1992) presents a model that substantially simplifies the cost and time associated with Portfolio Based Style Analysis. The method has become known as “Return Based Style Analysis”.³ It involves a multifactor model that determines a mutual fund’s effective exposure to the changes in the values of some predefined asset classes over time. We will see that by using this model in two steps, we get estimates that mimic the fund’s actual and policy weights in the predefined asset classes, which in turn can be used in the generalized framework by Brinson, Hood and Beebower to estimate a mutual fund’s security selection and market timing.

The framework we suggest in this chapter enables an investor to easily evaluate their manager’s track record. Furthermore, it gives the user an overview of one or several funds’ short- and long-term risk. This can in turn be used by the investor to judge whether the funds are suitable for their risk-tolerance. In order to illustrate the method, we will apply it on active Norwegian mutual funds that focus on Norwegian equity. For simplicity, we will look at mutual funds that only have long positions in the asset classes.

This chapter is organized as follows. Section 1.2 generalizes Brinson, Hood and Beebower’s framework in order to use it in our setting. In section 1.3, we look at what asset classes can be used to constitute a benchmark for Norwegian mutual funds. In section 1.4, we look at Sharpe’s model. In section 1.5 we combine Sharpe’s model with the generalized BHB-framework, and in section 1.6 we illustrate our framework using Norwegian mutual fund data. In section 1.7, we quickly summarize the framework’s weaknesses, and indicate what future research should focus on. Section 1.7 concludes this chapter.

² Listed as the most cited paper in the category “Global Finance and Investment Articles” by Institutional Investor Journals

³ Also known as “Returns-Based Style Analysis”, or simply just “Style Analysis”

1.2. Determinants of Mutual Fund Performance

The aim of this chapter is to develop a framework that can be used to estimate a mutual fund’s actual weights and policy weights in a set of asset classes, and estimate a mutual fund’s security selection and market timing. In this matter, a framework used by Brinson, Hood and Beebower (hereafter BHB) in the paper entitled “Determinants of Portfolio Performance” (1986) can be a useful starting point. Unfortunately, BHB’s framework is more appropriate to the data they have on hand than being suited as a generalized framework. Therefore we will generalize BHB’s ideas in order to be able to use their framework in our setting. We will see that if we have some predefined asset classes with associated indices, and have full knowledge of a mutual fund’s actual weights and policy weights in these predefined asset classes, we can use the framework to calculate the determinants of managerial performance; i.e., security selection and market timing.

Recall that capital markets provide 3 tools for mutual funds to employ in generating investment returns: asset allocation, security selection and market timing. Previously, we defined a benchmark as the standard in which a mutual fund’s return is evaluated against. If we assume that we have a benchmark that is determined by the mutual fund’s asset allocation (i.e., the fund’s long-term investment policy), we can decompose a mutual fund’s return according to Table 1:

TABLE 1:

Decomposing a Mutual Fund’s Performance

		Selection	
		Actual	Passive
Timing	Actual	(IV) Mutual Fund Return	(II) Benchmark and Timing Return
	Passive	(III) Benchmark and Security Selection Return	(I) Benchmark Return

$$\begin{aligned}
 \text{Market Timing} &= \text{Quadrant II} - \text{Quadrant I} \\
 &= \text{Quadrant IV} - \text{Quadrant III} \\
 \text{Security Selection} &= \text{Quadrant III} - \text{Quadrant I} \\
 &= \text{Quadrant IV} - \text{Quadrant II} \\
 \text{Excess Return} &= \text{Quadrant IV} - \text{Quadrant I}
 \end{aligned}$$

By default, we let Quadrant I represent the mutual fund’s benchmark return, i.e., the fund’s asset allocation.⁴ If the mutual fund has a current allocation (cf. Introduction/Appendix A)

⁴ This implies that the terms “benchmark return” and “return from asset allocation” can be used interchangeably

with equivalent risk as the benchmark, the effect of security selection and market timing should be zero provided that financial theory works. This means that the effect of security selection and market timing is zero in Quadrant I. If we add market timing to the benchmark, we get Quadrant II (given the obvious name “Benchmark and Timing Return”). When we add security selection to the benchmark, we get Quadrant III (called “Benchmark and Security Selection Return”). The sum of the benchmark return, security selection and market timing is the same as a mutual fund’s total return, as represented by Quadrant IV. This framework will be referred to as the generalized BHB-framework.

We define the sum of security selection and market timing as *excess return*. The decomposition implies that the excess return is equivalent to the difference between the mutual fund’s actual return (Quadrant IV) and that of the benchmark (Quadrant I). Furthermore, market timing is equivalent to the difference between Quadrant II and I, or equivalently, Quadrant IV – Quadrant III. Security selection can be calculated by subtracting Quadrant I from Quadrant III, or equivalently, Quadrant IV minus Quadrant II.

The framework in Table 1 shows how we can decompose the determinants of a mutual fund’s performance. Recall that the fund’s manager is not responsible for the amount of return generated by the asset allocation; this is the investor’s responsibility, since the investor chooses to bet on that particular risk. The manager is only responsible for the amount that is created in excess of the asset allocation. This implies that the determinants of managerial performance are measured through security selection and market timing. Since we can measure security selection by Quadrant IV – Quadrant II and market timing by Quadrant II – Quadrant I, we only need to quantify Quadrant IV, II and I in order to measure the determinants of managerial performance. This brings us to the question of how we should calculate the return of each quadrant in Table 1. In general, the total return of a mutual fund can be calculated with the following formula:

$$(1) \quad \text{Return of mutual fund in period } T = \sum_i (W_{i,T-1} \cdot \tilde{R}_{i,T})$$

Where:

$$W_{i,T-1} = \text{Weight in asset } i \text{ in period } T-1 = \frac{\text{Investment in asset } i \text{ in period } T-1}{\text{Total investments in period } T-1}$$

$$\tilde{R}_{i,T} = \text{Return of asset } i \text{ in period } T$$

The traditional view of asset allocation assumes that when investors place their money in mutual funds, the money will be diversified across many different asset classes.⁵ Ultimately, we are interested in the mutual fund's exposures to key asset classes. It may therefore be more sensible to apply formula (1) on asset classes instead of assets when calculating the return of a mutual fund. Hence, we suggest setting $W_{i,T-1}$ = weight in *asset class i* in period $T-1$, and $\tilde{R}_{i,T}$ = return of *asset class i* in period T . There are at least two reasons why we should do this. Firstly, categorization into asset classes allows us to process large amounts of information reasonably efficiently. The second reason is simply that it allows us to make a benchmark that reflects a fund's long-term investment policy, which in turn can be used to measure a fund's security selection and market timing.

We have previously defined two types of asset class weights, namely actual weights and policy weights. Recall that the actual weights are the mutual fund's proportions placed in particular classes of investments in the beginning of the current period, whereas the policy weights are the fund's long-term proportions placed in particular classes of investments. Assuming we are in period T , we can denote the actual weight and the policy weight for asset class i as $W_{a_i,T}$ and W_{p_i} respectively.⁶

There are also two types of asset class returns; namely passive return and active return. We define the passive return as the benchmark return for a given asset class. The passive return for asset class i in period T can be denoted as $\tilde{R}_{p_i,T}$, and its value is calculated by $\frac{\tilde{I}_{i,T} - \tilde{I}_{i,T-1}}{\tilde{I}_{i,T-1}}$, where $\tilde{I}_{i,T}$ = price for asset class i in period T as measured by an associated index. The *active return* is the mutual fund's actual return in a given asset class. The active return for asset class i at time T can be denoted as $\tilde{R}_{a_i,T}$. By combining these two returns with the two weights in all possible ways, we can measure each of the quadrants in Table 1.

⁵ This seems to be a realistic assumption for Norwegian Mutual funds, as they are required by law to invest in at least 16 different stocks. Furthermore, the actual weight in any company cannot exceed 10%

⁶ Although it could be more intuitive to denote the actual weight as $W_{a_i,T-1}$ in order to indicate that it is the proportion placed in asset class i in the beginning of the current period, we denote it as $W_{a_i,T}$. The reason for this is to avoid confusion in statements such as "the actual weight in period T is $W_{a_i,T-1}$ ". Now we can say "the actual weight in period T is $W_{a_i,T}$ ". Moreover, note that a fund's policy weights are independent of time. Because of this, its denotation has no time-subscript

Quadrant I represents the benchmark return, with no security selection or market timing. This suggests that the return of Quadrant I in period T can be calculated by multiplying each asset class' policy weight with their passive return in period T , and then summing this across all the asset classes.

Quadrant II represents the benchmark return plus market timing. Keep in mind that market timing is the strategic under- or overweighting of an asset class relative to its policy weight. Hence, the return of Quadrant II in period T can be calculated by multiplying each asset class' actual weight in period T with their passive return in period T , and then summing this across all the asset classes.

Quadrant III represents the benchmark return plus security selection. We defined security selection as the active selection of investments within an asset class. This suggests that the return of Quadrant III in period T can be calculated by multiplying each asset class' policy weight with the their active return in period T , and then summing this across all the asset classes.

Quadrant IV represents the mutual fund return, and consists of the benchmark return plus security selection and market timing. This implies that the return of Quadrant IV in period T can be calculated by multiplying each asset class' actual weight in period T with their active return in period T , and then summing this across all the asset classes.

The above arguments are expressed mathematically in Table 2:

TABLE 2:

Computing the Determinants of Mutual Fund Performance in period T :

		Selection	
		Actual	Passive
Timing	Actual	(IV) $\sum_{i=1}^n (Wa_{i,T} \cdot \bar{Ra}_{i,T})$	(II) $\sum_{i=1}^n (Wa_{i,T} \cdot \bar{Rp}_{i,T})$
	Passive	(III) $\sum_{i=1}^n (Wp_i \cdot \bar{Ra}_{i,T})$	(I) $\sum_{i=1}^n (Wp_i \cdot \bar{Rp}_{i,T})$

Wp_i = Asset class i 's policy weight
 $Wa_{i,T}$ = Asset class i 's actual weight in period T
 $\bar{Rp}_{i,T}$ = Asset class i 's passive return in period T
 $\bar{Ra}_{i,T}$ = Asset class i 's active return in period T

In order to make the framework operational, we segment the benchmark into n predefined asset classes. In BHB's analysis, the actual weights (i.e., $Wa_{i,T}$) for the predefined asset classes are specified in advance by the pension plans. In order to find the policy weights for each predefined asset class (i.e., Wp_i), BHB assume that the 10-year average actual weight of each predefined asset class is sufficient to approximate the long-term proportion. They argue that the reason for why this is a good approximation is that 10 years covers several business cycles, and that the average standard deviation of asset class holdings for common stocks and bonds is not high relative to the average amount held.

We have generalized BHB's framework in order to be able to use it in any setting where we know the fund's respective actual weights, policy weights, passive returns and active returns in a set of predefined asset classes. The reason for this is as follows. BHB segment the benchmark into common stocks, bonds, cash equivalents and a miscellaneous category, called "others".⁷ In BHB's analysis, the complete history of the contents in the "others" component is not available for all plans. Unfortunately, this complicates their framework. In order to make the framework appropriate to the data BHB have on hand, they measure managerial performance somewhat different than us. Just as in the generalized framework we have reviewed, BHB calculate market timing as Quadrant II – Quadrant I, and security selection as Quadrant III – Quadrant I. Moreover, they calculate excess return by Quadrant IV – Quadrant I. However, since BHB do not have the complete history of the contents in the "others" component, this is left as a residual when they subtract security selection and market timing from excess return. Hence, the "others" component can be measured by Quadrant IV – Quadrant III – Quadrant II + Quadrant I. In our setting, the effect of the "others" component is 0. This is because we assume that we know all the actual and policy weights of all the predefined asset classes, and that we know the passive and actual returns of these asset classes. In other words, we assume we know the complete history of the content of all asset classes.

Although our interest is in the generalized framework, let us quickly look at what BHB use their (specialized) framework for and what their results are. Using 91 large U.S. pension plans, BHB (mainly) answer the following questions:

⁷ The component called "others" contains convertible securities, international holdings, real estate, venture capital, insurance contracts, mortgage-backed bonds and private placements

- 1) How much of the pension plan's total return is attributed to security selection and market timing?
- 2) How much of the total variation in pension plan return is explained by the different quadrants over time?

In relation to question 1), BHB find that the pension plans on average lose by market timing and security selection. In relation to question 2), BHB find that the benchmark alone explains 93.6% of the total variation in actual return over time. This figure was seen as surprisingly high, and the results have been debated since (see e.g., Hood, 2005 or Xiong et al., 2010). Moreover, they find that quadrant II explains 95.3% of the variation over time, whereas quadrant III explains 97.8% of the variation over time. By definition, quadrant IV explains all the variation over time.

We will now formulate more quantitatively how the generalized BHB-framework can be used in our setting to measure a mutual fund's security selection and market timing. Previously we saw that we only need to quantify Quadrant IV, II and I in order to measure a mutual fund's security selection and market timing. For illustrational purposes, we will measure security selection and market timing for active Norwegian Mutual funds that focus on the Norwegian equity market. For simplicity, we will only look at mutual funds that have long positions in the n predefined asset classes. Moreover, we assume we know all the actual and policy weights of these predefined asset classes, and that we know their passive and actual returns. This implies that 100% of the fund's assets are invested in the n predefined asset classes both in the short-term and long-term. Sadly, we do not get the actual weights from the mutual funds like BHB do. However, in the next section we will get back to a method that enables us to get estimates that mimic a fund's actual and policy weights in a set of predefined asset class. Assuming we have the policy weights and the passive returns for n predefined asset class, the return of mutual fund m at time T in our setting can be formulated as follows:

$$(2) \quad \tilde{r}_{mT} = \left[\sum_{i=1}^n Wp_{mi} \cdot \widetilde{Rp}_{i,T} \right] + \tilde{s}_{mT} + \tilde{t}_{mT}$$

where $0 \leq Wp_{mi} \leq 1$ for $i=1 \dots n$, and $\sum_{i=1}^n Wp_{mi} = 1$

The terms in the bracket are Quadrant I in table 1, i.e. the benchmark that reflects the fund's asset allocation. The left hand side (i.e., \tilde{r}_{mT}) is the fund's actual return, i.e., Quadrant IV. The

difference between Quadrant IV and Quadrant I is security selection and market timing, or simply just excess return. The variables are defined as follows:

$$\begin{aligned}
\tilde{r}_{mT} &= \text{Mutual fund } m\text{'s actual return in period } T \\
\widetilde{R}p_{i,T} &= \text{Asset class } i\text{'s passive return in period } T \\
Wp_{mi} &= \text{Mutual fund } m\text{'s policy weight for asset class } i \\
\tilde{s}_{mT} &= \text{Mutual fund } m\text{'s return from security selection in period } T \\
\tilde{t}_{mT} &= \text{Mutual fund } m\text{'s return from market timing in period } T
\end{aligned}$$

Let us not stop with expression (2). Assuming we have the actual weights and the passive returns for the n predefined asset classes, we can formulate the return of mutual fund m in period T in our setting differently:

$$(3) \quad r_{mT} = \left[\sum_{i=1}^n Wa_{mi,T} \cdot \widetilde{R}p_{i,T} \right] + \tilde{s}_{mT}$$

where $0 \leq Wa_{mi,T} \leq 1$ for $i=1 \dots n$, and $\sum_{i=1}^n Wa_{mi,T} = 1$.

The terms in the bracket are Quadrant II in table 1, and the left hand side is Quadrant IV. $Wa_{mi,T}$ is mutual fund m 's actual weight in asset class i in period T .

The combination of expression (2) and (3) gives us the mathematical definition of market timing:

$$(4) \quad \tilde{t}_{mT} = \sum_{i=1}^n (Wa_{mi,T} - Wp_{mi}) \cdot \widetilde{R}p_{i,T}$$

From this formula, it becomes clear that market timing stems from the strategic under or overweighting of an asset class relative to its policy weight.

Clearly, equation (2) and (3) are formulations that can be used in this chapter to measure a mutual fund's security selection and market timing. However, to do these calculations, we need the following inputs:

- 1) n predefined asset classes that constitute our benchmark
- 2) The actual and policy weights of the predefined asset classes

One way of finding the actual and policy weights is to use Portfolio Based Style Analysis. As mentioned, this is an approach in which the characteristics of a fund over a period of time are

derived from the characteristics of the securities it contains at various points in time. The problem with this approach is that the time and cost with making and maintaining such a database is high. Sharpe's Return Based Style Analysis (1992) might in this matter serve as a better alternative. Before we look into the details of this model, we will use the next section to suggest what asset classes can constitute a benchmark for Norwegian mutual funds that focus on Norwegian equity.

1.3. The Asset Classes Constituting our Benchmark

In order to be able to use the generalized BHB-framework to solve our problem statements, we will need a certain number of adequate asset classes that constitute our benchmark. Sharpe (1992) argues that when making a benchmark, it is desirable that the asset classes which are used are i) mutually exclusive, ii) exhaustive, and iii) have returns that “differ”. In other words, a security should not be included in more than one asset class, as many securities as possible should be included in the chosen asset classes, and the asset classes should have low correlation.

In this section we will look at asset classes that fulfill as many of Sharpe’s objectives as possible, and can constitute a suitable benchmark for active Norwegian mutual funds that focus on Norwegian equity. We start by describing a common way of categorizing asset classes, namely styles.

1.3.1. Style Investing

When making portfolio allocation decisions, many investors first categorize assets into broad classes and then decide how to allocate their funds across these various asset classes. The asset classes that investors use in this process are sometimes called *styles*, and the process itself is known as *style investing*. Assets in a style usually share common characteristics which can be based in law (e.g., government bonds), markets (e.g., value and growth) or in fundamentals (e.g., commodities) (Barberis and Shleifer, 2003).

One very broad style could be domestic equity. In general, Norwegian mutual funds that associate themselves with the domestic equity style invest over 80% of their assets in Norway.⁸ In this matter, it might be sensible to categorize domestic equity into more distinct styles. The most popular styles that share common characteristics in the equity market are value, growth and market capitalization.

A growth investor has an approach focusing on earnings change, and may focus his or her attention on forecasting future earnings streams, with less attention to current price. A value

⁸ In order to be classified in one particular group (such as e.g., domestic mutual fund), the general rule is that the fund’s investment mandate should state that at least 80% of the fund’s assets are to be exposed within the investment universe the fund identifies itself with (Norwegian Fund and Asset Management Association)

investor will focus on dividend yield and/or price/earnings (P/E), and will look for relatively cheap or high yielding stocks, while paying less attention to a company's earnings prospects (Gerber, 1994). In other words, growth investors look for stocks with superior anticipated earnings growth while value investors look for undervalued stocks. Table 3 summarizes some of the typical attributes associated with these styles:

TABLE 3:

Characteristics of Growth and Value Style

Growth	Value
High historical earnings	High dividend yield
High expected earnings	High book/price ratio
High relative change in expected earnings	Low current P/E relative to historical P/E

Source: Gerber (1994)

Another popular way of categorizing equity is by market capitalization. Typical categorizations could be small-capitalization stocks (hereafter small-caps), mid-capitalization stocks (hereafter mid-caps) and large-capitalization stocks (hereafter large-caps).

Using U.S. data, Fama and French (1993) find that value stocks tend to outperform growth stocks, whereas Banz (1981) finds that small-caps have historically earned higher returns than large-caps. Based on these empirical anomalies, Fama and French (1993) construct a three-factor model to explain the difference in cross-sectional return of U.S. equity.⁹ It would be interesting to see whether these empirical anomalies apply to the Norwegian equity market as well. Say we decompose the Norwegian equity market into 5 styles: small-caps (S), mid-caps growth (MG), mid-caps value (MV), large-caps growth (LG) and large-caps value (LV). By using MSCI's Norwegian equity style-indices from 1995 to 2010,¹⁰ we get the yearly performance in each style as given by Table 4:

⁹ The 1st factor is the market risk premium

¹⁰ MSCI define value stocks using book value to price ratio, 12-months forward earnings to price ratio and dividend yield. Growth stocks are defined using long-term forward earnings per share (EPS) growth rate, short-term forward EPS growth rate, current internal growth rate, long-term historical EPS growth trend and long-term historical sales per share growth trend. The MSCI Small Cap Indices cover all investable small cap securities with a market capitalization below that of the companies in the MSCI Standard Indices. The MSCI Mid Cap Indices cover all investable mid cap securities, whereas the MSCI Large Cap Indices cover all investable large cap securities (MSCI, 2011)

TABLE 4:

Annual Returns: 5 Styles using MSCI's Indices. Period: 1995-2010

Year	S	MG	MV	LG	LV	High-Low Spread
1995	-1.6 %	11.3 %	4.5 %	3.3 %	-34.6 %	45.9 %
1996	27.3 %	19.7 %	33.9 %	34.8 %	-60.7 %	95.5 %
1997	15.0 %	15.5 %	50.1 %	8.9 %	-0.6 %	50.7 %
1998	-25.3 %	-33.3 %	-27.9 %	-2.4 %	-27.2 %	30.9 %
1999	58.1 %	30.8 %	47.2 %	5.8 %	31.1 %	52.3 %
2000	-9.4 %	5.4 %	19.4 %	-24.7 %	9.9 %	44.1 %
2001	-19.1 %	-31.2 %	-20.1 %	-10.2 %	0.3 %	31.6 %
2002	-54.9 %	-33.8 %	-24.2 %	-31.6 %	-15.5 %	39.4 %
2003	49.2 %	94.4 %	36.8 %	-4.2 %	30.3 %	98.5 %
2004	52.5 %	-62.2 %	37.8 %	-26.8 %	30.2 %	114.7 %
2005	52.1 %	24.7 %	34.7 %	21.3 %	44.2 %	30.8 %
2006	32.5 %	14.1 %	31.4 %	30.6 %	34.8 %	20.7 %
2007	-2.2 %	21.8 %	48.8 %	9.9 %	6.5 %	50.9 %
2008	-55.7 %	-67.6 %	-35.2 %	-55.3 %	-49.9 %	32.4 %
2009	84.6 %	59.4 %	55.1 %	55.7 %	45.0 %	39.6 %
2010	27.2 %	4.6 %	41.6 %	23.8 %	6.0 %	37.0 %
Arithmetic Average Yearly Return	14.4 %	4.6 %	20.9 %	2.4 %	3.1 %	50.9 %
Arithmetic Average Yearly Standard Deviation	40.9 %	42.3 %	31.0 %	28.2 %	33.0 %	

Source: Datastream and own analysis

The variability in return across the five styles from year-to-year is far greater than would have been encountered if groups with similar numbers of securities had been formed randomly. Just as in the U.S. equity market, small-caps perform better than large-caps on average, and value stocks do better than growth stocks. The table shows that the spread between the worst and the best performing asset class is on average over 50 percentage-points; in fact, in some periods the difference is close to or above 100 percentage-points. Hence, there is much to gain from choosing the right asset classes.

The results in Table 4 show that the risk (measured by arithmetic average yearly standard deviation) of the different styles vary substantially. Mid-caps growth stocks and small caps

stocks have been most volatile the last 16 years, and are around 10 percentage-points more volatile than mid-caps value stocks, large-caps growth stocks and large-caps value stocks.

We now touch upon a point that is important to stress. The manager who specializes to be e.g., a small-caps manager in the long run, is responsible for stock selection and market timing within the small-caps universe. If small-caps stocks are out of favor and underperform the overall market, a manager can still outperform the small-caps market. However, for us to be able to measure this, we need a benchmark that reflects the mutual fund's true long-run risk. Fortunately, this is accounted for in the generalized BHB-framework, since the benchmark is determined by mutual fund's asset allocation. The fact that the small-caps stocks underperform the market is the investor's responsibility, and not the manager's, since the investor chooses to bet on the particular style that follows with the asset allocation.¹¹

In Norway, most mutual funds use the Oslo Børs Mutual Fund Index (OSEFX) as their benchmark. If the components of OSEFX do not reflect the fund's asset allocation, this can induce moral hazard. To illustrate why, assume we study a mutual fund that does not utilize security selection or market timing. Provided that financial theory works, the manager only needs to increase the fund's risk to beat the benchmark on average. Recall that return associated with the fund's asset allocation is the investor's responsibility. If the fund claims that the benchmark reflects the fund's long-term risk, the investor will believe that the return that is created in excess of the benchmark is security selection and/or market timing. In reality it is just the payoff from extra risk in the mutual fund.

Based on the above arguments, it might make more sense to tailor-make a benchmark for each fund. In the next subsection we suggest what asset classes can be used to constitute a tailor-made benchmark for active Norwegian mutual funds.

1.3.2. Asset Classes for Norwegian Mutual Funds

For illustrational purposes, we will look at Norwegian mutual funds that focus on the Norwegian equity market. Although these mutual funds invest the majority of their assets in Norway, most have the ability to invest parts of their assets abroad. Therefore our benchmark

¹¹ Of course, this is under the weak assumption that the companies managing the mutual funds are just providers of mutual funds, not sellers/advisors

should include European and world equity indices. It would also have been desirable to include corporate bonds, but unfortunately, there are no Norwegian corporate bond indices. In order to capture the different styles that exist internally within Norwegian equity, we use the 5 indices we saw in the previous subsection.

A possible way of categorizing Norwegian Mutual fund's investable universe might be as follows: bills, intermediate and long-term government bonds, Norwegian equities (5 styles), European equities (excluding Norwegian equities), and world equities (excluding European equities). Table 5 describes the ten asset classes and the indices we use for the associated passive return series:

TABLE 5:

Asset Classes Constituting Benchmark for Norwegian Mutual Funds

Small-Caps (S)	World, ex. Europe (W)
Asset: Norwegian Small Capitalization Stocks	Asset: World Stocks excluding European Stocks
Index: MSCI Norway Small Capitalization*	Index: MSCI World ex. Europe*
Mid-Caps Growth (MG)	Europe, ex. Norway (E)
Asset: Norwegian Mid Growth Capitalization Stocks	Asset: European Stocks excluding Norwegian Stocks
Index: MSCI Norway Mid Growth Capitalization*	Index: MSCI Europe ex. Norway*
Mid-Caps Value (MV)	3 M
Asset: Norwegian Mid Value Capitalization Stocks	Asset: Cash-equivalents with less than 3 months to maturity
Index: MSCI Norway Mid Value Capitalization*	Index: Norway Interbank 3 Month until 08.01.2003 as proxy for Norway t-bill 3 month. Thereafter actual Norway t-bill 3 month.
Large-Caps Growth (LG)	3 Y
Asset: Norwegian Large Growth Capitalization Stocks	Asset: Intermediate-Term Government bonds
Index: MSCI Norway Large Growth Capitalization*	Index: Norway Benchmark 3 Year
Large-Caps Value (LV)	10 Y
Asset: Norwegian Large Value Capitalization Stocks	Asset: Long-Term Government bonds
Index: MSCI Norway Large Value Capitalization*	Index: Norway Benchmark 10 Year

*US price-index manually adjusted to NOK price-index

These time-series are collected via DataStream. Table 6 shows the correlation between these:

TABLE 6:

Return Correlation. Period: January 1995 – December 2010 (monthly observations)

	S	MG	MV	LG	LV	W	E	3 M	3 Y
Small-Caps (S)									
Mid-Caps Growth (MG)	49.6 %								
Mid-Caps Value (MV)	68.7 %	56.1 %							
Large-Caps Growth (LG)	45.8 %	35.8 %	34.1 %						
Large-Caps Value (LV)	53.7 %	39.6 %	46.2 %	38.4 %					
World, ex. Europe (W)	56.7 %	42.4 %	45.9 %	38.9 %	33.4 %				
Europe, ex. Norway (E)	66.0 %	45.7 %	57.0 %	45.8 %	41.5 %	83.7 %			
3 M	-32.3 %	-11.5 %	-21.5 %	-17.2 %	-16.6 %	-13.9 %	-21.7 %		
3 Y	-27.8 %	-5.5 %	-16.6 %	-14.0 %	-16.4 %	-13.8 %	-15.3 %	91.0 %	
10 Y	-18.1 %	-1.1 %	-12.5 %	-7.3 %	-17.3 %	-6.6 %	-4.5 %	70.0 %	88.9 %

We note that a few of these asset classes are highly correlated; especially the cash-equivalents and the bonds. Thus, Sharpe's criteria of having asset classes that "differ" might be violated in this case. We will later see what problems this can potentially cause.

1.3.3. Section Summary

In this section we have found 10 asset classes that can constitute a benchmark for Norwegian mutual funds, as well as 10 associated passive return series. In order to estimate a fund's security selection and market timing, we still need a method of estimating the policy and actual weights of these predefined asset classes. Hence, we will now look into Sharpe's infamous model from 1992.

1.4. Estimating a Mutual Fund's Weights using Return Based Style Analysis

In this section, we will look into a model which can potentially help us estimate a mutual fund's actual ($Wa_{mi,T}$) and policy (Wp_{mi}) weights; namely Sharpe's Return Based Style Analysis (hereafter RBSA). In this section we will describe the general model, its assumptions and its underlying properties, before we describe how it can be used in the generalized BHB-framework in the next section. This model has its foundation in a general multifactor-model; hence, in the next subsection, we give a short introduction of what multifactor-models are.

1.4.1. Multifactor-Models

Multifactor-models are a broad family of econometric models. Essentially, a multivariate process admits a multifactor representation if it can be approximately expressed as a function of another multivariate process of a smaller dimensionality. The general multifactor formulation of a model has to be clearly distinguished from the economic theory that might be behind it. In fact, multifactor models might be the expression of an economic theory as well as the result of an explicit econometric dimensionality reduction process (Focardi and Fabozzi, 2004). For instance, the Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965 and Mossin, 1966), the Arbitrage Pricing Theory (Ross, 1976) and the Intertemporal Capital Asset Pricing Model (Merton, 1973) are economic theories which happen to be expressed as factor models. This is however, not the general trend. In general, the process is purely statistical and not supported by theory. RBSA is an example of the latter.

As previously mentioned, the traditional view of asset allocation assumes that when investors place their money in mutual funds, the money will be diversified across many different asset classes. Hence, we are ultimately interested in the mutual fund's exposures to key asset classes. Given, say, v monthly realized returns on a mutual fund, along with comparable returns for a selected set of asset classes, one could simply use a multiple regression analysis with mutual fund returns as the dependent variable and asset class returns as the independent variables (Sharpe, 1992). Under certain statistical assumptions, which we soon will touch upon, the resulting slope coefficient can then be interpreted as the mutual fund's historic proportion in the asset classes. Equation (5) is an example of such a regression:

$$(5) \quad \tilde{r}_{mt} = \alpha_m + \sum_{i=1}^n \beta_{mi} \widetilde{R}p_{it} + \tilde{\varepsilon}_t; \quad t = T-v, T-v+1, \dots, T-1$$

where the variables and coefficients are as follows:

\tilde{r}_{mt}	=	Mutual fund m 's actual return in period t
α_m	=	Mutual fund m 's constant specific ¹²
β_{mi}	=	Mutual fund m 's sensitivity to asset class i
$\widetilde{R}p_{it}$	=	Asset class i 's passive return in period t
$\tilde{\varepsilon}_t$	=	Noise

We define the sum of the noise and mutual fund m 's constant specific as the tracking error, and denote it \tilde{e}_{mt} . Hence, model (5) simplifies to:

$$(6) \quad \tilde{r}_{mt} = \sum_{i=1}^n \beta_{mi} \widetilde{R}p_{it} + \tilde{e}_{mt}; \quad t = T-v, T-v+1, \dots, T-1$$

Sharpe sets $v = 60$ months in his analysis. However, in the first round we will stick to a generalized model. We define $\sum_{i=1}^n \beta_{mi} \widetilde{R}p_{it}$ as the *asset class portfolio series*. In order to estimate the sensitivities in model (6), we could use Ordinary Least Squares (OLS). This method minimizes the sum of square residuals, and is by far the most popular estimation method. We denote the estimated sensitivities as $\hat{\beta}_{mi}$ for $i = 1$ to n . For OLS to give unbiased estimates of the sensitivities, i.e., $E[\hat{\beta}_{mi}] = \beta_{mi}$ for $i = 1$ to n , the following 3 assumptions have to hold (Wooldridge, 2009):

- a) The mutual fund's return-process follows a model that is linear in its parameters
- b) In the sample (and therefore in the underlying time series process), no independent variable is constant nor a perfect linear combination of the other independent variables
- c) For each t , the expected value of the noise, given the explanatory variables for all time periods, is zero. Mathematically, $E(\tilde{\varepsilon}_t | \widetilde{R}p_{1t}, \dots, \widetilde{R}p_{nt}) = E(\tilde{\varepsilon}_t | \widetilde{R}p_t) = 0$ for $t = T-v, T-v+1, \dots, T-1$

The above assumptions say nothing about the efficiency of the estimated sensitivities. The following assumptions deal with this:

¹² Note that Sharpe does not mention the fund's constant specific in his paper at all, and just starts with equation (6)

- d) Conditional on the explanatory variables for all time periods, the variance of the noise is the same for each t . Mathematically, $Var(\tilde{\varepsilon}_t | \widetilde{\mathbf{R}}\mathbf{p}_t) = \sigma^2$ for $t = T-v, T-v+1, \dots, T-1$ (i.e., noise process is homoscedastic)
- e) Conditional on the explanatory variables for all time periods, the noise in two different time periods are uncorrelated for each t . Mathematically, $Cov(\tilde{\varepsilon}_t, \tilde{\varepsilon}_s | \widetilde{\mathbf{R}}\mathbf{p}_t) = 0$ for all $t \neq s$ (i.e., no autocorrelation)

Assumptions a) – e) ensure that OLS estimators are the best linear, unbiased estimators conditional on the explanatory variables for all time periods. In order to do inference and estimation, the previous assumptions with the addition of the following assumption have to hold:

- f) For each t , the noise $\tilde{\varepsilon}_t$ is independent of the explanatory variables for all time periods and is independently and identically distributed as $N(0, \sigma^2)$

Note that assumption f) implies assumption c), d) and e). Under assumption f), t statistics can be used for testing statistical significance of individual explanatory variables, and F statistics can be used to test for joint significance.

Equation (6) is a static, linear regression model, where both mutual fund returns and asset class returns are assumed to be stationary stochastic processes. A stochastic process is a sequence of random variables indexed by time (Wooldridge), as indicated by the tildes in model (6). Formally, a stochastic process $\{y_t : t = 1, 2, \dots, n\}$ having a finite mean and variance is *covariance-stationary* if for all t and $t-s$,

$$E(y_t) = E(y_{t-s}) = \mu$$

$$Var(y_t) = Var(y_{t-s}) = \sigma^2$$

$$Cov(y_t, y_{t-s}) = \gamma_s$$

This implies that we have to assume that the mutual fund returns and asset class returns have a constant mean, constant variance and time-invariant covariance in order to run them on model (6). We say that a stationary process is integrated of order 0. A process that is not stationary, but needs to be differentiated n times to get stationary, is said to be integrated of order n . Moreover, a process that is not stationary is said to be *unit root*.

To sum up: if we assume that the 10 predefined asset classes (cf. Table 5, pg. 21) are not constant nor linear combinations of each other, we will get unbiased estimates of the fund's historic proportions in the asset classes as long as the mutual fund and asset class return-series are stationary, and that for each t , the expected value of the noise, given the explanatory variables for all time periods, is zero.

1.4.2. From Linear Regression to Quadratic Programming

In this subsection we will illustrate how we go from linear regression to the technique used in RBSA: quadratic programming. In this matter, we will use the 10 asset classes and their associated indices (as defined in Table 5) as passive return-series. These series run from 1995 to 2010. Before these return series can be used in model (6), we have to ensure that they are stationary. In appendix B, we test the ten asset classes for unit root using a Dickey Fuller test. The result suggests that all asset classes except for bills (3M) and bonds (3Y and 10Y) are stationary. In cases where the dependent and the independent variable are integrated of different orders, regression analysis gives meaningless results (Enders, 2010).¹³

In the long run, it is realistic to assume that interest rates have a constant mean, constant variance and time-invariant covariance, simply because they cannot increase or decrease infinitely. This would imply that bills and bonds are stationary. The main reason for why the Dickey Fuller test suggests that bills and bonds are unit root is due to the fact that interest-rates have mainly just decreased in the period under study. Because business cycles may take more than 15 years to finish, we would probably get a different picture if we had used longer time-series. Based on these arguments, we chose to include bills and bonds in the regression.¹⁴

Table 7 illustrates the steps from linear regression to quadratic programming using the Norwegian mutual fund DnB Nor Norge (I) as example.¹⁵ We use DnB Nor Norge (I)'s monthly returns from January 2001 through December 2010 as the dependent variable (i.e.,

¹³ This situation seemingly arises if the mutual fund's return-series is stationary. This is also referred to as "nonsense regression". This should not be confused with "spurious regression". Spurious regression is a situation where the estimates appear to be significant, but the results are without any economic meaning. This situation arises when the dependent variable is integrated of the same order as the independent variable and where the residual sequence contains a stochastic trend

¹⁴ This is also done in Sharpe's analysis (1992)

¹⁵ For a description of how DnB Nor Norge (I)'s return-series are calculated, see subsection 1.6.1. Appendix E shows that DnB Nor Norge (I)'s return-series is stationary

$v = 120$), with the corresponding returns for the ten previously defined indices serving as independent variables.

TABLE 7:

Regression and Quadratic Programming Results
DnB Nor Norge (I). Period: January 2001 – December 2010

	Unconstrained Regression	Constrained Regression	Quadratic Programming
Small Cap (S)	37 % **	36 %	38 %
Mid Cap Growth (MG)	6 % **	6 %	6 %
Mid Cap Value (MV)	13 % **	13 %	13 %
Large Cap Growth (LG)	4 %	3 %	3 %
Large Cap Value (LV)	34 % **	35 %	34 %
World, ex. Europe (W)	-4 %	-5 %	0 %
Europe, ex. Norway (E)	14 %	15 %	5 %
3 M	-244 %	-66 %	0 %
3 Y	198 %	47 %	0 %
10 Y	331 %	15 %	0 %
Total	389 %	100 %	100 %
R-squared	93.93 %	93.87 %	93.72 %

** Significant at a 1 % level

* Significant at a 5 % level

The column entitled “Unconstrained Regression” shows the results obtained when applying equation (6) using Ordinary Least Squares (OLS). The first ten rows show the estimated sensitivities (i.e., $\hat{\beta}_{(DnB)i}$), expressed as percentages. A few of these are significant at a 1% level.¹⁶ The sensitivities associated with bills and bonds are suspiciously high, although not significantly different from 0. The sum of the coefficients is shown after the first ten rows, followed by the R^2 . A substantial portion (93.93%) of the monthly variance in the fund’s returns is explained by the ten asset classes.

Recall that we restrict ourselves to use analyze Norwegian mutual funds that only have long positions in the asset classes, and where 100% of the money is invested in the 10 asset classes over time. However, in the unconstrained regression, the coefficients do not sum to 100%, but to 389%. Furthermore, several of the coefficients are inconsistent with the mutual fund’s

¹⁶ If we assume that for each t , the noise $\tilde{\varepsilon}_t$ is independent of the explanatory variables for all time periods and is independently and identically distributed as $N(0, \sigma^2)$, t and F statistics can be used

actual policy not to have short positions in the asset classes.¹⁷ Hence, the results are not sensible in our setting.

The column titled “Constrained Regression” reports the results of a multiple regression analysis similar to the first, but with one added constraint: the coefficients are required to sum to 100%. The reduction in R^2 is slight (from 93.93% to 93.87%), but the inconsistency between the coefficients and the fund's investment policy still remains, since several of the sensitivities are negative.

The last column entitled “Quadratic Programming” reports the results of an analysis where each coefficient is constrained to lie between 0% – 100% and the sum is again required to be 100%. This causes R^2 to decrease slightly to 93.72%. Nevertheless, the coefficients now conform more closely to the reality of the fund’s investment style, making the resulting characterization more likely to provide meaningful results with out-of-sample data. This method, proposed by Sharp in 1992, has become known as Return Based Style Analysis. In the next subsection, we will look into the details of this method.

1.4.3. Return Based Style Analysis

The example with DnB Nor Norge (I) shows that by adding constraints reflecting minimal information about what investments the fund actually makes, one can obtain greatly improved results. Let us take a closer look at how we get the coefficients associated with the column entitled “Quadratic Programming” in table 7. If we re-arrange model (6), we get an expression for the tracking-error:

$$(7) \quad \tilde{e}_{mt} = \tilde{r}_{mt} - (\sum_{i=1}^n \beta_{mi} \tilde{R}p_{it}); \quad t = T-v, T-v+1, \dots, T-1$$

In order to get results that conform closely to the reality of a fund’s investment style, Sharp argues that we should infer as much as possible about a fund’s sensitivities to the variations in the return of the predefined asset classes during the period studied (we will get back to a geometric interpretation of what Sharp means with this later). If we assume that the stochastic

¹⁷ It should be noted that DnB Nor Norge (I) has limited ability to go short in securities through the use of derivatives. Furthermore, they have small amounts of debt in their portfolio (Source: DnB NOR). However, for simplicity, this is ignored

processes in (7) are stationary, we can find such sensitivities by minimizing the variance of the tracking error for each t with respect to the sensitivities:

$$(8) \quad \text{Minimize } \text{Var}(\tilde{\epsilon}_{mt}) \text{ for each } t \text{ wrt. } \beta_{mi}, i = 1 \dots n$$

where

$$\begin{aligned} \text{Var}(\tilde{\epsilon}_{mt}) &= \text{Var}(\tilde{\epsilon}_t) = \\ & \text{Var}(\tilde{r}_{mt}) + \sum_{i=1}^n \beta_{mi}^2 \text{Var}(\widetilde{R}p_{it}) + 2 \sum_{i=1}^{n-1} \sum_{j=i+1}^n \beta_{mi} \beta_{mj} \text{Cov}(\widetilde{R}p_{it}, \widetilde{R}p_{jt}) - \\ & 2 \sum_{i=1}^n \beta_{mi} \text{Cov}(\tilde{r}_{mt}, \widetilde{R}p_{it}) \end{aligned}$$

In order to apply Sharpe's method on our dataset, we replace the theoretical moments with the empirical moments. Under the assumption that the stochastic processes are stationary, the mean, variance and autocorrelations can usually be well-approximated by sufficiently long time averages based on the single set of realizations (Enders, 2010). Using return-series for $t = T-v, T-v+1, \dots, T-1$, we denote the empirical moments as follows:

- Sample mean return of mutual fund m :

$$\bar{r}_m = \frac{1}{v} \cdot \sum_{t=T-v}^{T-1} \tilde{r}_{mt}$$

- Sample mean return of asset class i :

$$\overline{R}p_i = \frac{1}{v} \cdot \sum_{t=T-v}^{T-1} \widetilde{R}p_{it}$$

- (Unbiased) Sample variance of mutual fund m :

$$S_r^2 = \frac{1}{v-1} \cdot \sum_{t=T-v}^{T-1} (\tilde{r}_{mt} - \bar{r}_m)^2$$

- (Unbiased) Sample variance of asset class i :

$$S_{Ri}^2 = \frac{1}{v-1} \cdot \sum_{t=T-v}^{T-1} (\widetilde{R}p_{it} - \overline{R}p_i)^2$$

- (Unbiased) Sample covariance between asset classes i and j :

$$S_{Ri,Rj} = \frac{1}{v-1} \cdot \sum_{t=T-v}^{T-1} (\widetilde{Rp}_{it} - \overline{Rp}_i)(\widetilde{Rp}_{jt} - \overline{Rp}_j)$$

- (Unbiased) Sample covariance between mutual fund m and asset class i :

$$S_{r,Ri} = \frac{1}{v-1} \cdot \sum_{t=T-v}^{T-1} (\widetilde{r}_{mt} - \overline{r}_m)(\widetilde{Rp}_{it} - \overline{Rp}_i)$$

We define the sample variance of the tracking error as s^2 . If we replace $Var(\widetilde{r}_{mt})$ by S_r^2 , $Var(\widetilde{Rp}_{it})$ by S_{Ri}^2 , $Cov(\widetilde{Rp}_{it}, \widetilde{Rp}_{jt})$ by $S_{Ri,Rj}$ and $Cov(\widetilde{r}_{mt}, \widetilde{Rp}_{it})$ by $S_{r,Ri}$, our problem becomes as follows:

$$(9) \quad \text{Minimize } s^2 \text{ wrt. } \beta_{mi}, i = 1 \dots n$$

where

$$s^2 = S_r^2 + \sum_{i=1}^n \beta_{mi}^2 S_{Ri}^2 + 2 \sum_{i=1}^{n-1} \sum_{j=i+1}^n \beta_{mi} \beta_{mj} S_{Ri,Rj} - 2 \sum_{i=1}^n \beta_{mj} S_{r,Ri}$$

We can now add the constraints stating that the sensitivities are to lie between 0% – 100% and that the sum of the sensitivities is required to be 100%. Based on the constraints, we can get estimates of the sensitivities by solving the following problem:

$$(10) \quad \text{Minimize } s^2 \text{ wrt. } \beta_{mi}, i = 1 \dots n, \text{ subject to}$$

$$\sum_{i=1}^n \beta_{mi} = 1$$

$$\beta_{mi} \geq 0, i=1 \dots n$$

where

$$s^2 = S_r^2 + \sum_{i=1}^n \beta_{mi}^2 S_{Ri}^2 + 2 \sum_{i=1}^{n-1} \sum_{j=i+1}^n \beta_{mi} \beta_{mj} S_{Ri,Rj} - 2 \sum_{i=1}^n \beta_{mj} S_{r,Ri}$$

The presence of a non-negativity constraint for the sensitivities implies that problem (10) cannot be solved with regression analysis, but requires the use of a numerical method to solve it. In the column entitled “Quadratic Programming” in table 7, we have used MATLAB’s quadratic programming algorithm in a coding made by Andreas Steiner (available through the MATLAB central) to solve the problem.¹⁸ The name “Quadratic Programming” comes from the fact that the objective function is quadratic and the constraints are linear. Because we have used styles to categorize the asset classes, the sensitivities are simply referred to as *style-*

¹⁸ Sharpe uses the gradient method. For referees, see Sharpe (1987). For an exact solution, one can implement Markowitz’ critical line method (see Markowitz, 1987)

weights.¹⁹ Since the method only uses return-series, it is referred to as *return based style analysis*, or simply just *style-analysis*.

Let us now return back to equation (8). If we assuming that $E(\tilde{\epsilon}_t | \widetilde{\mathbf{R}}\mathbf{p}_t) = 0$ for $t = T-v, T-v+1, \dots, T-1$, we can rewrite the term $2 \sum_{i=1}^n \beta_{mi} \text{Cov}(\tilde{r}_{mt}, \widetilde{R}p_{it})$ as follows:²⁰

$$2 \sum_{i=1}^n \beta_{mj} \text{Cov}(\tilde{r}_{mt}, \widetilde{R}p_{it}) = 2 \sum_{i=1}^n \beta_{mi}^2 \text{Var}(\widetilde{R}p_{it}) + 4 \sum_{i=1}^{n-1} \sum_{j=i+1}^n \beta_{mi} \beta_{mj} \text{Cov}(\widetilde{R}p_{it}, \widetilde{R}p_{jt})$$

Inserting this into (8), we can the problem:

$$(11) \quad \text{Minimize } \text{Var}(\tilde{\epsilon}_{mt}) \text{ for each } t \text{ wrt. } \beta_{mi}, i = 1 \dots n$$

where

$$\text{Var}(\tilde{\epsilon}_{mt}) = \text{Var}(\tilde{r}_{mt}) - \sum_{i=1}^n \beta_{mi}^2 \text{Var}(\widetilde{R}p_{it}) - 2 \sum_{i=1}^{n-1} \sum_{j=i+1}^n \beta_{mi} \beta_{mj} \text{Cov}(\widetilde{R}p_{it}, \widetilde{R}p_{jt})$$

As before, we replace the theoretical moments with the empirical moments. Thus, problem (11) becomes as follows:

$$(12) \quad \text{Min } s^2 \text{ wrt. } \beta_{mi}, i = 1 \dots n$$

where

$$s^2 = S_r^2 + \sum_{i=1}^n \beta_{mi}^2 S_{Ri}^2 - 2 \sum_{i=1}^{n-1} \sum_{j=i+1}^n \beta_{mi} \beta_{mj} S_{Ri,Rj}$$

If $E(\tilde{\epsilon}_t | \widetilde{\mathbf{R}}\mathbf{p}_t) = 0$ for $t = T-v, T-v+1, \dots, T-1$, formulation (9) and (12) will be equal. However, in the presence of the non-negativity constraint on the style-weights, the estimated noise process is likely to be correlated with some of the return-series of the asset classes (Sharpe, 1992). This will make formulation (9) and (12) different. It is important to note that RBSA has a foundation in formulation (9), and not (12).

Until now we have interpreted the sensitivities as historic proportions in the asset classes. Unfortunately, the consequence of correlation between the estimated noise process and return-series of the asset classes is that we cannot make correct estimates of the historic proportions of total assets invested in the individual asset classes. Nevertheless, because we minimize the

¹⁹ Sharpe simply uses the term “weights”

²⁰ We replace \tilde{r}_{mt} by $\sum_{i=1}^n \beta_{mi} \widetilde{R}p_{it} + \tilde{\epsilon}_{mt}$;

variance of the tracking error for each t , the style-weights still have an interpretation. In the next subsection, we will look at how we should interpret the style-weights.

Failure of statistical assumptions means that conventional tests of statistical significance invoked to evaluate the likely performance of the model are violated, which makes true out-of-sample tests the only reliable means of evaluating the efficacy of the approach. However, in subsection 1.5.6., we will see that it is possible to approximate the confidence intervals of the style-weights.

1.4.4. The Duck Theorem

Sharpe argues that the best sets of sensitivities are the ones where the variance of the tracking error for each t is the least. In this subsection we will analyze why this method is preferred and how we should interpret the style-weights when we use this method.

Consider the extreme case, where the variance of the tracking error for each t equals zero. This is only true if the difference between the mutual fund's return series and the asset class portfolio series (*i. e.*, $\sum_{i=1}^n \beta_{mi} \widetilde{R}p_{it}$) is constant for each t , meaning that the return-series run parallel in each of the v months under investigation. For each t , where $t = T - v, T - v + 1, \dots, T - 1$, the following statements are equivalent:

$$Var(\tilde{e}_{mt}) = Var(\tilde{\epsilon}_t) = 0$$

\leftrightarrow

$$\tilde{r}_{mt} - \sum_{i=1}^n \beta_{mi} \widetilde{R}p_{it} = \alpha_m$$

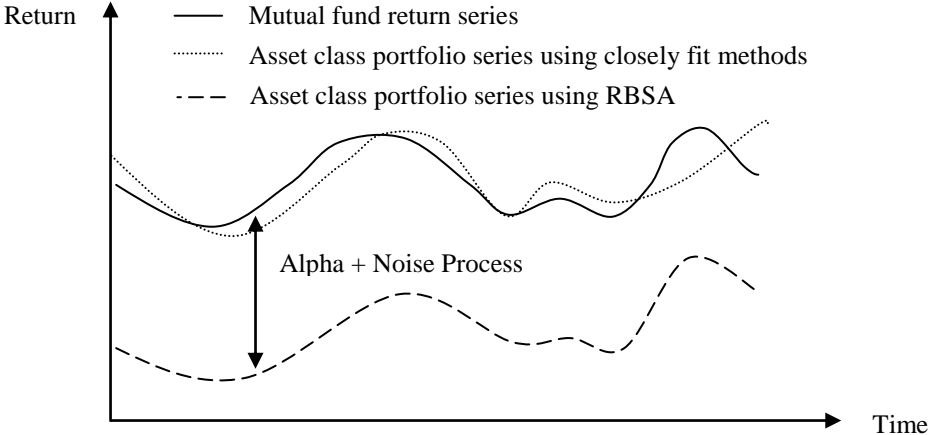
In this optimal case, the asset class portfolio series resemble the exact *shape* of the mutual fund's return series, with the tracking error resulting in a constant addition or subtraction of the value over the asset class portfolio series. Unfortunately, the constraints in problem (10) make this situation highly unlikely to occur in practice.

In more regular situations, RBSA determines the style-weights in such a way that the asset class portfolio series is able to closely resemble the behavior of the mutual fund's return series for each t , with the tracking error resulting in a near-constant addition or subtraction of the

value over the asset class portfolio series for each t . This is what Sharpe means when he emphasizes that the goal of his analysis is infer as much as possible about the mutual fund’s sensitivities to the variations in the return of the predefined asset classes during the period studied. Note that the objective of RBSA is not to minimize the average value of the difference between the mutual fund’s return series and that of the asset class portfolio series; neither does it aim to minimize the sum of the squared differences. Such methods would yield a very different geometric interpretation, as they would try to make the asset class portfolio series as close to the mutual fund’s return series as possible. In other words, such methods would “make the fund look bad” (or good) (Sharpe, 1992). Figure 1 illustrates the difference between RBSA and methods that try to closely fit the asset class portfolio series to the mutual fund’s return series:²¹

FIGURE 1:

RBSA versus closely fit methods



Source: Thomas Becker (2003)

To sum up: the implication of correlation between the estimated noise process and the return-series of the asset classes is that we cannot interpret the estimated style-weight $\hat{\beta}_{mi}$ as the proportion of total assets invested in asset class i in the period $t = T-v$ to $T-1$. However, because we minimize the variance of the tracking error for each t , the estimated style-weight can be interpreted as a weight that reflects the fund’s behavior in asset class i in the period $t = T-v$ to $T-1$. Hence, the style-weights have an interpretation.

²¹ RBSA uses discrete sequences of returns in the discrete time--period $T-v \dots$ to $T-1$. However, for illustrational purposes, the graph assumes continues sequences of return in a continuous time-period from $T-v$ to $T-1$

In table 7, RBSA shows that DnB Nor Norge (I) has an exposure of 37.8% in small-caps, 6.2% in mid-caps growth, 13.1% in mid-caps value, 3.2% in large-caps growth, 34.4% in large-caps value and 5.3% in European stocks. The correlation between the estimated tracking error and the return-series of the asset classes implies that the estimates are likely to be biased. Therefore we cannot interpret them as the mutual fund's proportions in the asset classes over the 10 year period. Nevertheless, what we get from the analysis is that DnB Nor Norge (I) behaves as if it invests in 37.8% small-caps, 6.2% mid-caps, ..., etc. To phrase it as Sharpe does: "if it walks like a duck and talks like a duck, for all important purposes, it is a duck" (1995).

1.4.5. Evaluating the Asset Classes

Once the styles-weights have been estimated, we can evaluate the efficacy of the asset classes by measuring the portion of the variance of mutual fund m 's return that is explained by the predefined asset classes:

$$(13) \quad R_{QP}^2 = \frac{S_r^2 - s^2}{S_r^2} = 1 - \frac{s^2}{S_r^2}$$

where S_r^2 = sample variance of mutual fund m and s^2 = sample variance of the tracking error.

Note that s^2 comes from the formulation in problem (9), and not problem (12). In the case with DnB Nor Norge (I), $R_{QP}^2 = 93.72\%$. It is important to recognize that (13) indicates only the extent to which a specific model fits the data at hand. A better test of the usefulness of any implementation is its ability to explain performance out-of-sample.

1.4.6. An Investor's Effective Asset Mix

When we have estimated the styles-weights of the individual mutual funds, one can easily estimate the effective asset mix when using multiple mutual funds. Let ω_m represent the proportion of the investor's portfolio invested in mutual fund m , then the overall portfolio return at time t is:

$$(14) \quad \tilde{R}_{p,t} = \sum_m \omega_m \cdot \tilde{r}_{m,t}$$

Now model (6) can be inserted in (14) to yield the following linear relationship:

$$(15) \quad \tilde{R}_{p,t} = [\sum_m \omega_m \beta_{m1}] \tilde{R}_{p1t} + [\sum_m \omega_m \beta_{m2}] \tilde{R}_{p2t} + \dots + [\sum_m \omega_m \beta_{mn}] \tilde{R}_{pnt} + [\sum_m \omega_m \tilde{e}_{mt}]$$

Now $[\sum_m \omega_m \beta_{mi}]$ is the portfolio's exposure to the asset class i . Sharpe notes that when the tracking errors across the different managers are uncorrelated, diversification across different fund managers will substantially reduce the variance of the aggregate non-style components and thus increase the proportion of the variance attributable to asset class selection. Even if some tracking errors are correlated, the use of multiple fund managers will often lead to a large reduction in the aggregate non-style components.

1.4.7. Approximating the Confidence Intervals for the Style-Weights

Since the non-negativity constraint in problem (10) generally causes the noise process to be correlated with the return-series of the asset classes, we cannot get a closed form expression of the confidence interval. However, an approximation made by Lobosco and DiBartolomeo (1997) helps us understand what factors affect the confidence-interval of the style-weights. Consider the extent to which the estimated style-weights do not match the true style-weights:

$$\hat{\beta}_{mi} = \beta_{mi} + \Delta\beta_{mi}$$

where:

$$\begin{aligned} \hat{\beta}_{mi} &= \text{Mutual fund } m\text{'s estimated style-weight for asset class } i \\ \beta_{mi} &= \text{Mutual fund } m\text{'s (true) style-weight for asset class } i \\ \Delta\beta_{mi} &= \text{Amount of error in mutual fund } m\text{'s estimated style-weight for} \\ &\quad \text{asset class } i \end{aligned}$$

As argued previously, $\hat{\beta}_{mi}$ represents a weight that reflects the fund's behavior in asset class i in the period $t = T-v$ to $T-1$. Lobosco and DiBartolomeo show that the standard deviation of the estimated weight can be approximated by the following formula:

$$(16) \quad \sigma_{\Delta\beta_{mi}} = \frac{\sigma_{\hat{e}}}{\sigma_{B_i} \sqrt{v-k-1}}$$

where:

$$\sigma_{\hat{e}} = \text{Standard deviation of the estimated tracking error } (\hat{e}_{mt}) \text{ in the period } t = T-v \dots T-1 \text{ (observable). We let } \hat{e} \text{ be an abbreviation of } \hat{e}_{mt}$$

σ_{B_i}	=	Standard deviation of asset class i 's return series not being attributable to the other asset classes in period $t = T-v \dots T-1$ (observable)
v	=	Length of the return series
k	=	Number of asset classes with nonzero style-weights

For the proof of this formula and how we can measure σ_{B_i} , see Appendix C. The problem with this method is that it is only valid in the special case when none of the weights are either zero or 1. This is because the formula is based on Taylor expansions, which cannot be used to obtain asymptotic distributions of the style-weights on the boundary of the parameter space. Kim, White and Stone (2005) propose a method that accounts for this. However, for illustrative purposes, Lobosco and DiBartolomeo's formula is suitable for us. From the formula, one can see that the confidence interval for a style-weight increases if:

- a) The standard deviation of the estimated tracking error ($\sigma_{\hat{\theta}}$) increases
- b) The length of the return series (v) decreases
- c) The "independence" of asset class i from the other asset classes (σ_{B_i}) decreases

Point a) was thoroughly illustrated in subsection 1.4.4.: when the shape of a manager's return-series is perfectly mimicked, the variance of the tracking error for each t is zero. In this case the estimated style-weight is exactly the same as the true style-weight.²²

As point b) shows, increasing the number of returns used decreases the standard deviation of the estimated weight. However, as we will see in the next section, this will also affect the interpretation of the style-weights.

Point c) is an important point to thoroughly investigate. As an example of how things can go wrong, consider convertible bonds. A convertible bond has the characteristics of both bonds and stocks, implying that convertible bonds are dependent on bond and stock return. From equation (16) we see that the inclusion of convertible bond would increase the style-weight's standard deviation due to the low value of $\sigma_{B_{convertible\ bonds}}$. This means that style-analysis can only reliably attribute portfolio returns to the portions of the asset class return that are themselves not attributable to the returns of the other asset classes (Lobosco and DiBartolomeo, 1997).

²² In fact, in this special situation, the estimated weights are the fund's proportions in the asset classes

It could be argued that mid-capitalization stocks are a combination of small-capitalization stocks and large-capitalization stocks. Table 4 shows that mid-caps growth stocks do indeed have smaller average return than small-caps stocks, and larger average return than large-caps growth stocks; making it a linear combination of the two. On the other side, we see that mid-caps value stocks have larger average return than both small-caps and large-cap value stocks. Based on this, mid-caps stocks are not a direct linear combination of small caps stocks and large-cap stocks.

We might also expect that the high correlation between bonds and bills will cause the confidence intervals of bonds and bills to increase and that RBSA will have trouble seeing the difference between these asset classes. However, in general, the 10 asset classes we have included seem to be suitable for illustrational purposes.

1.4.8. Section Summary

In this section, we have reviewed RBSA. We have seen how RBSA originates from multifactor-models, how we should interpret the style-weights and we have looked at the factors that affect the confidence interval of style-weights. In the next section we will use RBSA in the generalized BHB-framework to estimate a mutual fund's actual ($Wa_{mi,T}$) and policy (Wp_{mi}) weights in our 10 asset classes.

1.5. Combining Style-Analysis and the BHB-framework

In this section, we will see that by using RBSA in two-steps, we will be able to estimate two sets of weights that are closely related to a fund's actual and policy weights. This will enable us to use the generalized BHB-framework to estimate a mutual fund's security selection and market timing.

1.5.1. A Two-Step Approach using RBSA

In the previous section, we reviewed RBSA because we need a method that can help us estimate the actual and policy weights in a set of asset classes. In the generalized BHB-framework, we define the policy weights to be the long-term proportions placed in particular classes of investments, whereas the actual weights are the mutual fund's proportions placed in particular classes of investments in the beginning of the current period.

Unfortunately, by using RBSA, the style-weights do not represent proportions anymore, but weights that mimic the behavior of the mutual fund in the given period. However, if we assume that weights that reflect the fund's short-term and long-term behavior are good estimates of a fund's actual and policy weights respectively, we can use RBSA to estimate the actual and policy weights. We assume this, and the rest of the analysis in this chapter is based on this assumption.

Let us now define a mutual fund's *actual style-weights* as exposures in particular classes of investments that mimic the fund's behavior in the short-run. Moreover, we define *policy style-weight* as exposures in particular classes of investments that mimic a mutual fund's behavior in the long-run. We let the actual style-weights and the policy style-weights to be our estimates of the fund's actual weights and policy weights respectively.

As previously mentioned, BHB argue that the 10-year mean average actual weight of each asset class is sufficient to approximate the policy weights. They argue that the reason for why this is a good approximation is that 10 years covers several business cycles, and that the average standard deviation of asset class holdings for common stocks and bonds is not high relative to the average amount held. Equivalently, one can argue that running RBSA with 10

years with return-data ($v = 120$ months) is sufficient to estimate a fund's policy weights. Based on this, we denote the fund's policy style-weights as follows:

β_{mi}^P = Mutual fund m 's policy style-weight for asset class i in period T . This is found using RBSA for $t = T - 120, T - 119, \dots, T - 1$.

Recall that equation (2) and (3) enable us to calculate a fund's security selection and market timing as long as we have the actual and policy weights. If one accepts that the policy style-weights are used as estimates of the fund's policy weights, we can insert the policy style-weight in formula (2) to model the return of mutual fund m at time T as follows:

$$(17) \quad \tilde{r}_{mT} = \left[\sum_{i=1}^n \beta_{mi}^P \cdot \widetilde{Rp}_{i,T} \right] + \tilde{s}_{mT} + \tilde{t}_{mT}$$

Since we use RBSA as a mean of estimating the policy weights, we know that $0 \leq \beta_{mi}^P \leq 1$ for $i=1 \dots n$, and $\sum_{i=1}^n \beta_{mi}^P = 1$ (cf. problem (10), pg. 30).

The terms in the bracket in formula (17) are defined as the *style-benchmark*. This is our estimate of Quadrant I in the generalized BHB-framework. The left hand side is Quadrant IV. The difference between the mutual fund's return and style-benchmark is our estimate of the fund's excess return, which consists of security selection and market timing. Sharpe (1992) argues that an adequate benchmark should ideally be I) a viable alternative, II) not easily beaten, III) low in cost and IV) identifiable before the fact. In section 1.3, we found 10 indices that compromise the benchmark for Norwegian mutual funds. A style-benchmark that consists of these indices seems to be a viable alternative. Furthermore, by using RBSA, we get a style-benchmark that is not easily beaten, due to the fact that the asset class portfolio series closely follows the movement of the mutual fund for each t . Moreover, the style-benchmark is easy and cheap to replicate since it is comprised of 10 well-known indices. By using RBSA with return-series from period $T-120$ to $T-1$ instead of $T-119$ to T , we also ensure that the benchmark is identified in advance of time T . All in all, the style-benchmark seems like an adequate benchmark.

Note that the use of RBSA implies that the policy style-weights are time-varying, something we know that policy-weights are not. Clearly, this is a weakness, but it should not pose a large problem: we will later see that the policy style-weights remain quite stable over time, simply because we use 10 years with return-data to find the weights.

Recall that we only need to quantify Quadrant IV, II and I in order to measure the fund's security selection and market timing. We have already got a measure of Quadrant IV (it is just the mutual fund's return), and Quadrant I is estimated in formula (17). All that remains is to estimate Quadrant II.

In the generalized BHB-framework, the return of Quadrant II in period T is calculated by multiplying each asset class' actual weights (in period T) with their passive return (in period T), and then summing this across all the asset classes. As previously argued, we now replace the actual weights with the fund's actual style-weights.

Recall that the actual weights are the fund's proportions placed in particular classes of investments in the beginning of the current period. Since we use RBSA as a mean of estimating these weights, it is important to note that RBSA requires at least 2 time-periods to estimate the actual weights.²³ At first though, running RBSA with 2 months with return-data ($v = 2$) would seem like a good idea. This means that the model uses return-series from the period $T-2$ to $T-1$ to estimate the actual weights at time T .²⁴ However, in subsection 1.4.7., we saw that decreasing the length of the return series means that the noise in the estimated style-weights increases. Hence, using only 2 months with return-data to estimate the actual weights is probably a bad strategy. A good estimate balances between having small enough time-series that capture the fund's short term movements, but long enough time-series to avoid excessive noise.

Sharpe argues that an adequate benchmark should not be easily beaten. This implies that the style-benchmark should minimize the difference between Quadrant IV and Quadrant I. With similar arguments, an adequate estimate of Quadrant II should minimize the difference between Quadrant IV and Quadrant II. Let us for now call the difference between Quadrant IV and Quadrant II in period T for the *prediction error* and denote it \tilde{e}_{mT} . As we have already argued, the value of this is affected by the time length used in RBSA. Let us call the time length that on average minimizes the prediction error for Q . Only when we set $v = Q$ in

²³ To calculate the unbiased sample variance, we need at least 2 periods with return-data. If we only use one period with data, the denominator of the unbiased sample variance will be zero

²⁴ We want the weights to be identified in advance of time T . Hence, we run the model using data from the period $T-2$ to $T-1$ instead of the period $T-1$ to T

RBSA, the prediction error is an adequate estimate of the security selection. We denote the actual style-weights as follows:

β_{mi}^A = Mutual fund m 's actual style-weight for asset class i in period T . This is found using RBSA for $t = T - Q, T - Q + 1, \dots, T - 1$

If the mutual fund utilizes market timing, Q should be considerably smaller than 120 months in order to capture short-term movements, but longer than 2 months in order to avoid noise. For funds that avoid market timing, the actual style-weights should be equivalent to the policy style-weights. In these cases, the confidence-intervals of the style-weights will just decrease as we increase the time length of the return-series. This implies that on average, the prediction error should decrease as ν increases. In the next subsection, we will describe a stepwise approach that can be used to find Q .

By replacing the actual weights with the actual style-weights in formula (3), we can measure the return of mutual fund m at time T as follows:

$$(18) \quad \tilde{r}_{mT} = \left[\sum_{i=1}^n \beta_{mi}^A \cdot \widetilde{Rp}_{i,T} \right] + \tilde{s}_{mT}$$

Since we use RBSA as a mean of estimating the actual weights, we know that $0 \leq \beta_{mi}^A \leq 1$ for $i=1 \dots n$, and $\sum_{i=1}^n \beta_{mi}^A = 1$. The terms in the brackets are our estimate of Quadrant II in the BHB-framework, and the difference between the mutual fund's return (Quadrant IV) and Quadrant II is the estimated security selection.

We now have two equations (equation 17 and 18), and two unknowns (security selection and market timing). This makes it easy to estimate a fund's security selection and market timing in a given time period.

1.5.2. Finding the Optimal Time Length for Describing a Mutual Fund's Short-Term Movements

In this section we will look at a stepwise method that allows us find the optimal time length for describing a mutual fund's short-term movements. As before, we denote the optimal time length Q . We suggest the following stepwise approach:

- 1) Set ν equal to some small number ≥ 2
- 2) For the out-of-sample period $i = T$ to F (F for future, where $T < F$) proceed as follows:
 - a. Find the style-weights in period i by running RBSA with return-data from time $i - \nu$ until $i - 1$
 - b. Use the style-weights in period i together with the return of the passive return-series in period i to calculate the return of Quadrant II in period i
 - c. Measure the prediction error (i.e., Quadrant IV – Quadrant II) in time period i . We denote this prediction error as $\tilde{e}_{m(i)}$
- 3) Evaluate the performance of ν from period T to F using a performance evaluation such as e.g., the mean square prediction error: $MSPE = \frac{\sum_{i=T}^F (\tilde{e}_{m(i)})^2}{F-T+1}$ (Enders, 2010)
- 4) Increase the value of ν , and repeat steps 1-3. Proceed with this until $\nu = 120$

The time length ν that minimizes the MSPE would be the optimal time length for describing a mutual fund's short-term movements, i.e., Q . In the next section we will look at a practical example where this method is used.

1.5.3. Section Summary

In this section we have assumed that weights that reflect the fund's short-term and long-term behavior are good estimates of a fund's actual and policy weights respectively. This implies that we can estimate the fund's actual and policy weights using RBSA in two steps. These estimates can in turn be used in the generalized BHB-framework to estimate a fund's security selection and market timing.

In the next section, we will illustrate the framework using Norwegian mutual fund data.

1.6. Estimating Determinants of Risk and Managerial Performance using Norwegian Mutual-Fund Data

In this section we will illustrate how the two-step approach can be used to estimate a mutual fund's actual weights and policy weights using the passive return-series of the 10 predefined asset classes (cf. Table 5, pg. 21). Furthermore, we will illustrate how we can use these estimated weights to estimate security selection and market timing. All illustrations are done using Norwegian mutual-fund data.

1.6.1. Mutual Fund Data

We will look at current, active Norwegian mutual funds that focus on Norwegian equity, and that only have long positions. In order to estimate the funds' asset allocation by RBSA, we need close to 10 years with return-data. Based on all these prerequisites, we can analyze 46 mutual funds. A list of these mutual funds is given in Appendix D. Using a unit-root test; we find that all these mutual funds have stationary return-series (see appendix E).

We use a fund's net asset value (NAV) to compute mutual-fund returns. NAV is the fund price excluding redemption fees and sales charges. It is gross taxes, and net of management fees and costs. Furthermore, it assumes that dividends are reinvested in the fund. We calculate the return from period $T-1$ to T as follows:

$$\tilde{R}_{T-1,T} = \frac{NAV_T}{NAV_{T-1}} - 1$$

The time-series are collected via Børsprosjektet NHH and Bloomberg.²⁵

1.6.2. Finding Q for Norwegian Mutual Funds

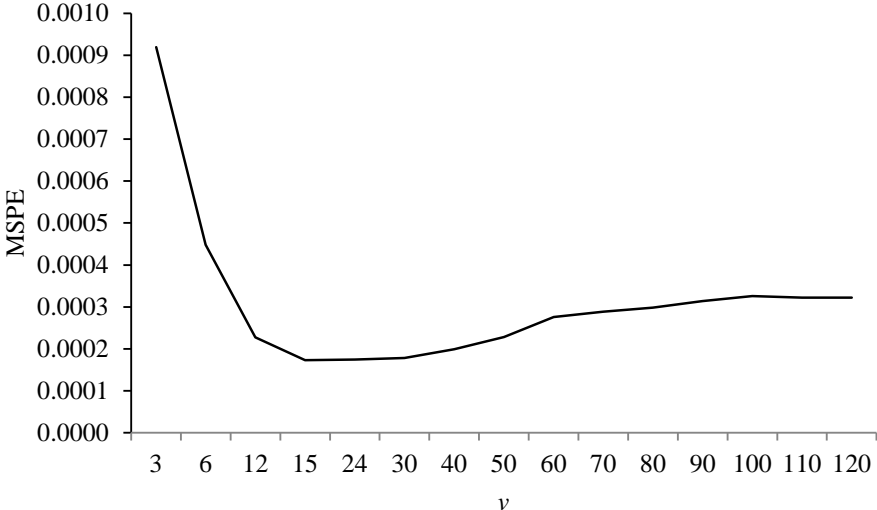
In this section we will illustrate how we can use the stepwise-approach in section 1.5.2. to estimate the optimal time length for describing a mutual fund's short-term movements. We let the out-of-sample period be January 31st 2007 (i.e., T) to December 31st 2010 (i.e., F). Hence, we have 48 out-of-sample observations for each mutual fund and for each value of ν (length of return-series in RBSA). We vary ν from 3 to 120. The time length that minimizes the MSPE in the period from T to F will be the optimal time length for describing a mutual fund's short-term movements, and will be denoted Q .

²⁵ Courtesy of Petter Slyngstadli in Holberg Forvalting

Let us first look at a mutual fund that seems like it utilizes market timing; namely DnB Nor Norge (I). We let the y-axis represent the MSPE, and the x-axis show the variation in ν .

FIGURE 2:

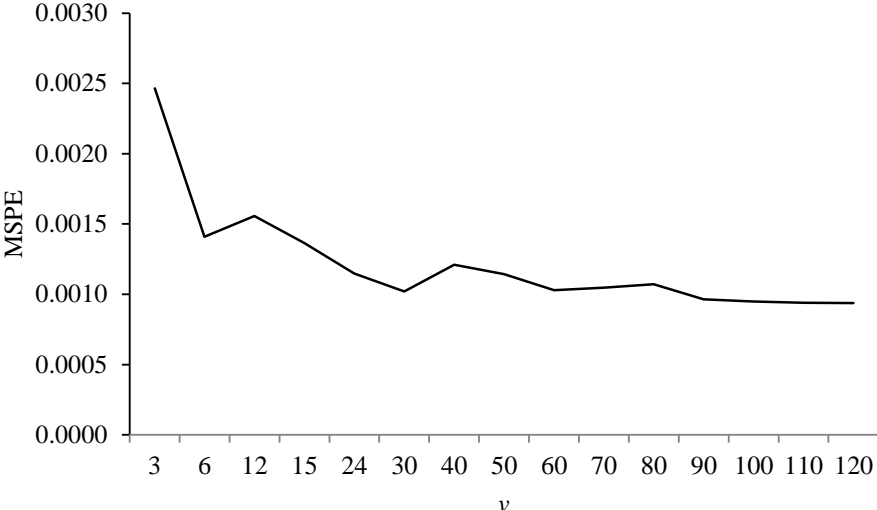
MSPE for varying ν for DnB Nor Norge (I)



In this case, the short-term style-weights are able to predict better than the long-term style-weights. More specifically, the style-weights in the region $\nu = 12-30$ months have the lowest MSPE. If the mutual fund does market timing, it is natural to infer that the short-term style-weights have a smaller prediction error than the long-term style-weights on average. Therefore it seems like DnB Nor Norge (I) tries to time the market. Let us look at a mutual fund that does not seem to utilize market timing, namely Alfred Berg Gambak:

FIGURE 3:

MSPE for varying ν for Alfred Berg Gambak



In this case, the MSPE decreases as ν increases, and the short-term style-weights do not predict better than long-term style-weights. Recall that for funds that avoid market timing, the prediction error should on average decrease as ν increases. This seems to be the case for Alfred Berg Gambak; hence, it seems like it tries to avoid market timing.

Let us now generalize our framework, and use the stepwise-approach to estimate what Q is on average for Norwegian mutual funds. We analyze each of the 46 mutual funds in Appendix D. As in the above examples, we use the out-of-sample period from January 31st 2007 (i.e., T) to December 31st 2010 (i.e., F). In order to find the optimal time length for describing Norwegian mutual fund's short-term movement, where we vary ν from 3 to 120,²⁶ and rank each time length based on the mean, median and mode MSPE.²⁷ Table 8 shows the result of the analysis:

TABLE 8:

Ranking of ν for 46 Norwegian Mutual Funds
Using Out-of-sample Period from 2007 to 2010

Month	Mean	Median	Mode
3	15	15	12
6	14	14	12
12	13	13	8
15	12	12	5
24	3	2	1
30	1	1	2
40	2	3	3
50	6	4	6
60	7	8	4
70	8	11	12
80	10	10	8
90	11	9	8
100	9	7	12
110	4	5	8
120	5	6	6

²⁶ Note that we were not able to find the MSPE up to $\nu = 120$ for all mutual funds, due to the fact that a few of these funds do not have long enough history. This might have affected the mode somewhat, although the effect is probably not large, since very few mutual funds have the lowest MSPE as ν approaches 120

²⁷ The mean refers to the following procedure: for each mutual fund, we rank each ν based on MSPE (where the lowest MSPE is the best). Thereafter we rank each ν based on the average ranking. The Median refers to the same procedure, but where we use median instead of mean. The mode refers to the following procedure: for each mutual fund, we rank each ν based on MSPE. Thereafter we count how many times each ν has the best ranking across the 46 mutual funds. The ν with the highest count gets the best ranking

From this analysis, we see that $\nu = 30$ months has the smallest mean and median MSPE. On the other hand, $\nu = 24$ yield the best result when we count which ν appears most frequently with the lowest MSPE. The list with the 46 mutual funds consists of funds that avoid market timing, and funds that utilize market timing. Hence, it is natural to assume that the mean and median in Table 8 are slightly higher than they would have been if we had taken out all the funds that avoid timing. Hence, we suggest setting $Q = 24$ months to estimate Norwegian mutual funds' actual style-weights.

Unfortunately, Sharpe's paper does not consider market timing at all. In fact, when Sharpe describes RBSA, he uses 60 months of return-data, and defines the difference between the mutual fund's return in month T and that of the asset class portfolio series as security selection. In this section we have seen that this can only be true as long the mutual fund avoids market timing, or alternatively if Q is 60 months. Table 8 seems to give little evidence to support such claims.

The problem with using 60 months in RBSA is that the style-weights from such an analysis are not best able to reflect the mutual fund's short-term movements. I.e., it is not best able to explain the fund's short-term risk. Therefore such weights should not be used by investors as a decision basis.

If 60 months is used in RBSA, and Q for U.S. funds is less than 60 months, the difference between the mutual fund's return in month T and that of the asset class portfolio series will not only be security selection; it will also partly consist of market timing. Sharp finds that U.S. mutual funds on average have negative security selection. As we will see in the next chapter, Norwegian mutual funds loose on average by timing the market. If this is also the case in the U.S. market, Sharp's framework underestimates the funds' abilities to pick stocks.

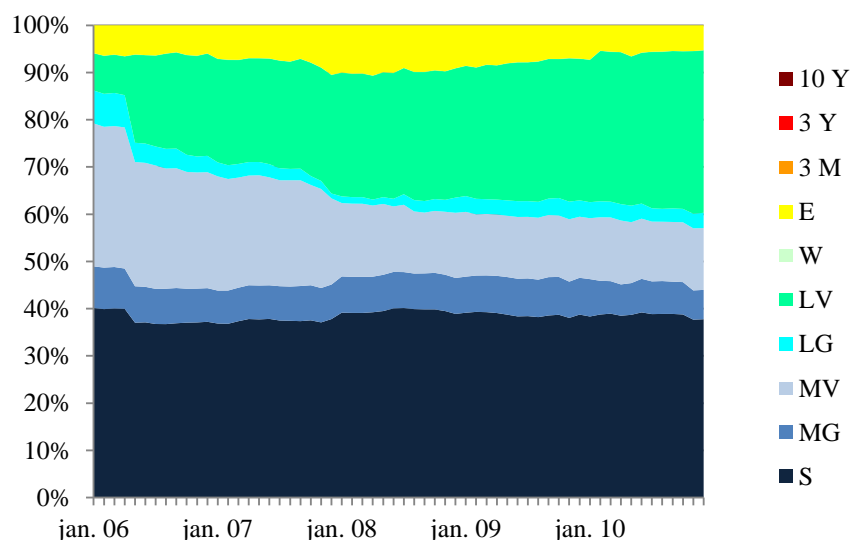
1.6.3. Estimating a Mutual Fund's Determinants Risk

The actual style-weights and policy style-weights constitute our estimates of a fund's determinants of short-term and long-term risk respectively. In this subsection we will exemplify how the framework can be used to analyze a mutual fund's short-term and long-term risk over time.

Let us analyze a mutual fund which we are familiar with; namely DnB Nor Norge (I). We will investigate the fund's policy style-weights from January 2006 to January 2011. In this matter, we use RBSA with 120 months of return-data to estimate the fund's style-weights in January 31st 2006, i.e., return-data from January 31st 1996 to December 31st 2005. The same analysis is run until we get the fund's policy style-weight in January 31st 2011 (which we get by using RBSA with data from January 31st 2001 to December 31th 2010). This dynamic analysis is often referred to as a *rolling style composition*. Figure 4 show's DnB Nor Norge (I)'s estimated policy style-weights in this period. This figure is often referred to as a *rolling window*:²⁸

FIGURE 4:

120 Months Rolling Style Composition Showing Policy Style-Weights over Time.
 Period: Jan. 2006 – Jan. 2011. Mutual Fund: DnB Nor Norge (I)²⁹



Previously we mentioned that the use of RBSA implies that the policy style-weights are time-varying, something we know that policy-weights are not. Figure 4 shows that this does not seem to be a large problem, due to the stability of the style-weights over time. This indicates that the policy style-weights are suitable estimates for the fund's asset allocation. The figure shows that DnB Nor Norge (I) behave as if they have had an asset allocation focusing on large-caps value stocks (approximately 30%), small-caps stocks (approximately 40%), and the

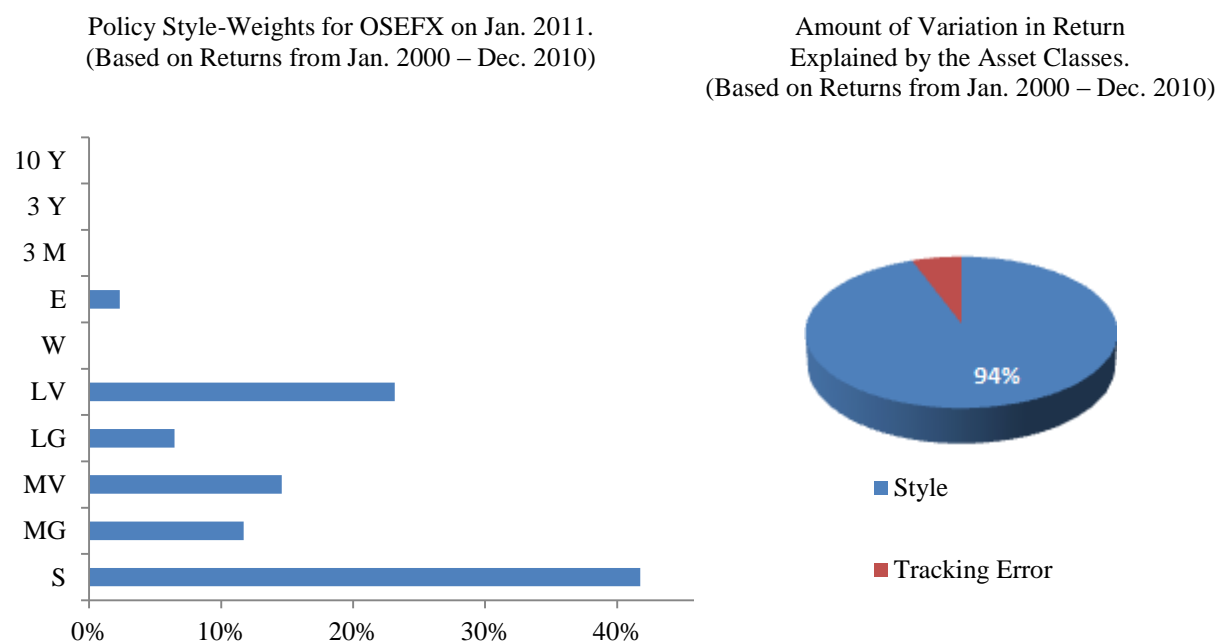
²⁸ Note that the style-weights are calculated using discrete returns, and not log-returns. This would imply that we should minimize the geometric variance in RBSA. However, for simplicity we minimize the arithmetic variance. Such differences are nevertheless negligible

²⁹ We have abbreviated the names of the asset classes in this figure (and all the subsequent ones using similar portrayals) as follows: S = small-caps, MG = mid-caps growth, MV = mid-caps value, LG = large-caps growth, LV = large-caps value, W = world, ex. Europe, E = Europe, ex. Norway, 3M = cash-equivalents with less than 3 months to maturity, 3 Y = intermediate-term government bonds, 10 Y = long-term government bonds

remaining on mid-caps growth stocks, mid-caps value stocks and European stocks. The fact that the analysis shows that the fund behaves as if it invest up to 10% in European stocks is in line with their prospectus, which states that the fund may invest up to 20% in foreign companies not listed or traded on a Norwegian market. Note that every point in the figure represents the results of RBSA using a different set of 120 monthly returns.³⁰ In general, every set has $\nu-2$ months in common with its predecessor (here: 118 months in common). The point at the far right of the diagram represents the style described when the 120 months ending in December 2010 are analyzed; i.e., the fund’s policy style-weights in January 2011. This corresponds to the styles we saw in the column entitled “Quadratic Programming” in table 7.

Previously we mentioned that most mutual funds use the Oslo Børs Mutual Fund Index (OSEFX) as their benchmark. This can be problematic if it does not reflect the true long-term risk of the fund. Let us therefore estimate OSEFX’s policy style-weights on January 31st 2011 to proxy OSEFX’s long-term risk:

FIGURE 5:



Using this as a proxy for long-term risk, we see that OSEFX behaves as if it is exposed to long-term risk from small-caps (~42%), mid-caps growth stocks (~12%), mid-caps value stocks (~15%), large-caps growth stocks (~6%), large-caps value stocks (~23%) and

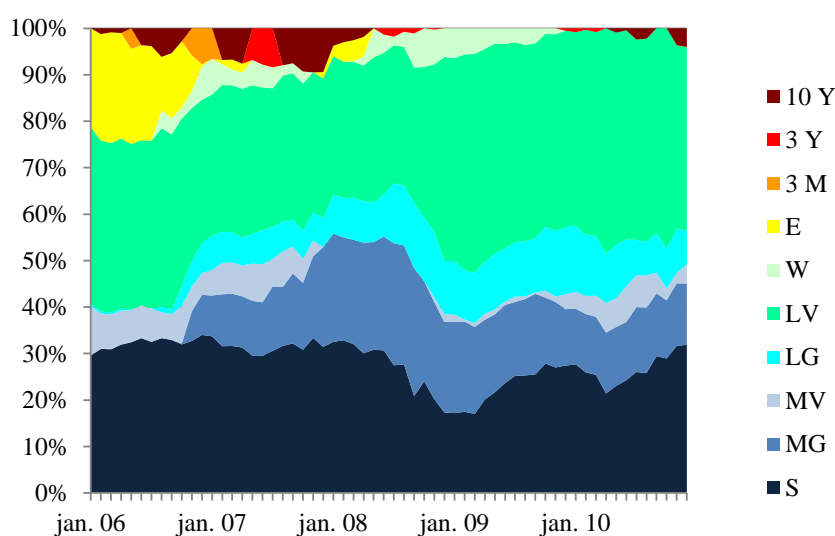
³⁰ Every point on the figure’s vertical axis represents one month. The associated style-weights in this month are represented by the different colors on the vertical axis at that point

European stocks (~2%).³¹ These weights explain 94% of the OSEFX’s variation in return from 2000 – 2010. In table 7, we found DnB Nor Norge (I)’s policy style-weights for January 2011. If we use this as a proxy for the fund’s long-term risk, we see that the fund behaves as if it has an asset allocation consisting of small-caps (~38%), mid-caps growth stocks (6%), mid-caps value stocks (~13%), large-caps growth stocks (~3%), large-caps value stocks (~34%) and European stocks (~5%). If we were to use OSEFX as a benchmark to DnB Nor Norge (I), we would not be able to reflect the fund’s true long-term risk. For instance, DnB Nor Norge (I) behaves as if it is exposed to more large-caps value stocks than OSEFX, whereas OSEFX is seemingly exposed to more of the risk from mid-caps growth stocks than DnB Nor Norge (I). In Table 4, we saw that the average risk and return across the 5 equity styles vary considerably. This implies that the only appropriate benchmark is a risk-adjusted benchmark that is that is able to mimic the mutual fund’s long-term investment policy. This is exactly why we use RBSA to find the fund’s policy style-weights.

Let us now look at DnB Nor Norge (I)’s short-term risk from January 2006 to January 2011. In this matter, we use 24 months with return-data, implying that we have to use RBSA with return-data from January 31st 2004 to December 31st 2005 in order to estimate the fund’s actual weights in January 31st 2006. Figure 6 shows the estimated actual weights of DnB Nor Norge (I) from January 2006 to January 2011 using a rolling style-decomposition:

FIGURE 6:

24 Months Rolling Style Composition Showing Actual Style-Weights over Time.
 Period: Jan. 2006 – Jan. 2011. Mutual Fund: DnB Nor Norge (I)



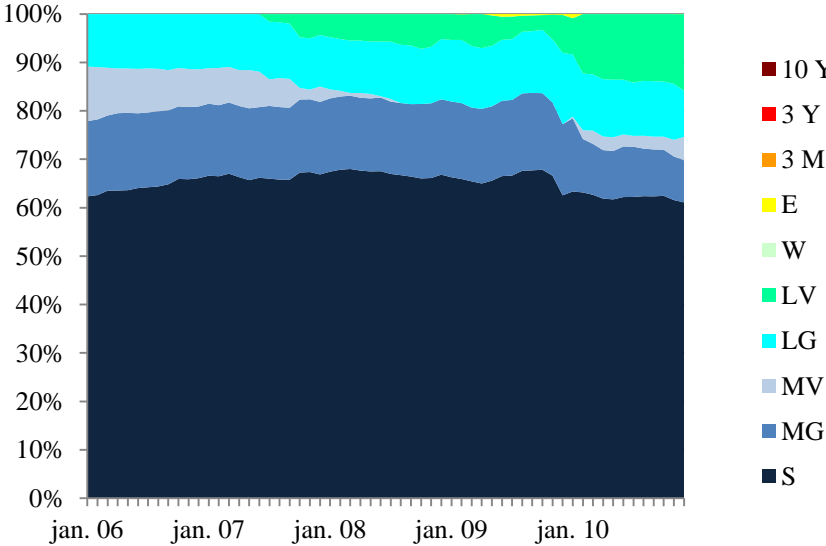
³¹ The fact that OSEFX is exposed to the European equity market is natural, as a large amount of the companies on Oslo Børs have operations outside Norway

The figure shows that the actual style-weights deviate from the policy style-weights (cf. figure 4, pg. 47) over time. Such deviations point in the direction that DnB Nor Norge (I) utilizes market times. Furthermore, figure 6 indicates that the fund acts as if it utilizes bonds and bills in the short run. This is in line with the fund’s prospectus.

In the next subsection, we will see how we can use the actual and policy style-weights to decompose the fund’s excess return. Before this is done, let us switch to another mutual fund we have looked upon earlier; namely Alfred Berg Gambak. Figure 7 shows the policy style-weights of Alfred Berg Gambak from January 2006 to January 2011:

FIGURE 7:

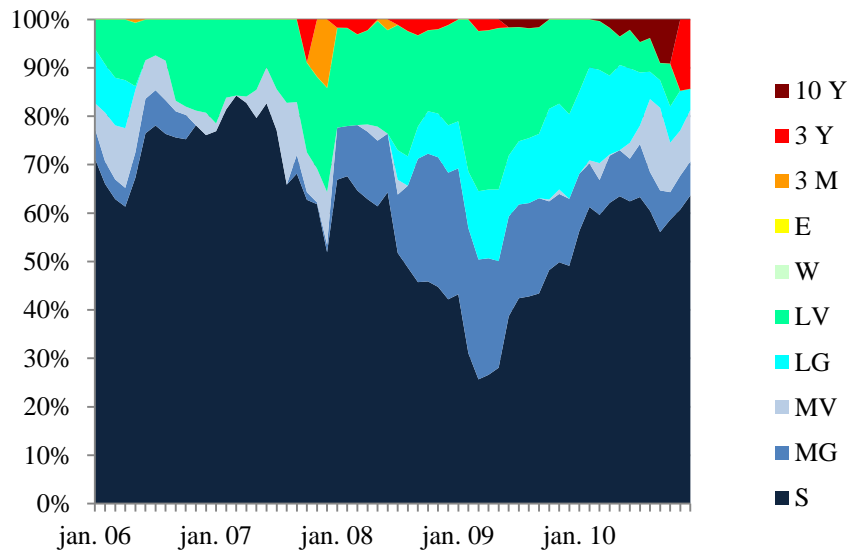
120 Months Rolling Style Composition Showing Policy Style-Weights over Time.
 Period: Jan. 2006 – Jan. 2011. Mutual Fund: Alfred Berg Gambak



The figure is relatively stable over time, indicating that the policy style-weights are suitable estimates for the fund’s asset allocation. The figure shows that Alfred Berg Gambak acts as if it has an asset allocation focusing on Norwegian small-caps stocks (approximately 60%), with the remaining assets evenly spread among mid-caps growth stocks, large-caps growth stocks, and large-caps value stocks. Using the weights in Figure 5 as a proxy for OSEFX’s long-term risk, we see that Alfred Berg Gambak behaves as if it is exposed to more small-caps stocks, and less large-caps value stocks in the long-run. This indicates that OSEFX is not suitable as a benchmark for Alfred Berg Gambak, because OSEFX would not be able to mimic the fund’s long-term investment policy. Let us look at Alfred Berg Gambak’s short-term risk from January 2006 to January 2011, as illustrated by Figure 8:

FIGURE 8:

24 Months Rolling Style Composition Showing Actual Style-Weights over Time.
Period: Jan. 2006 – Jan. 2011. Mutual Fund: Alfred Berg Gambak



Previously we argued that it seemed like the fund did not utilize market timing because the MSPE just decreased as the time length in the return-data increased. This would imply that the actual style-weights are equivalent to the policy style-weights. However, by comparing Figure 8 with Figure 7, we see that this does not seem to be the case. This could imply that the fund does indeed try to time the market, or it could simply imply that 24 months is not enough time to get rid of the noise in Alfred Berg Gambak’s return-data.

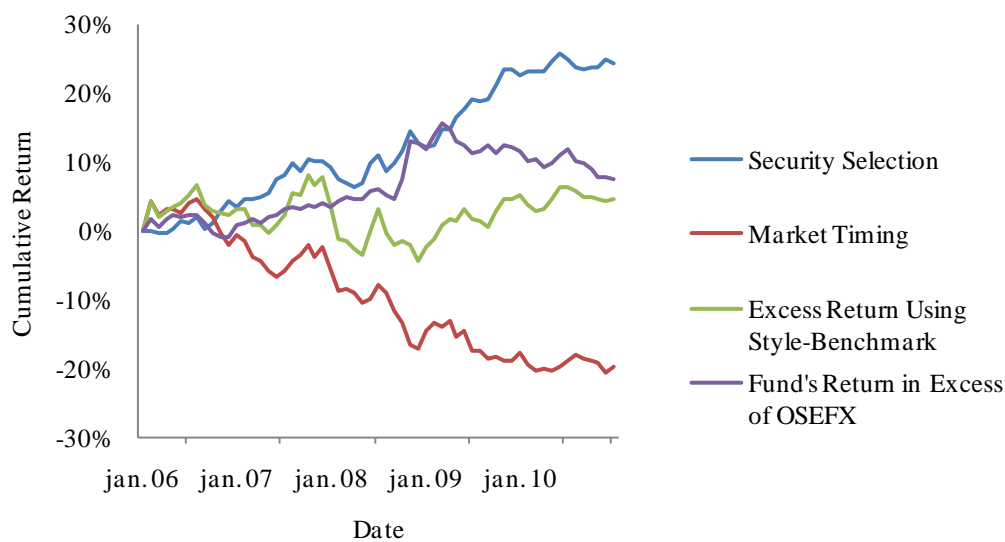
1.6.4. Estimating a Mutual Fund’s Determinants of Managerial Performance

Having obtained estimates of the monthly actual and policy weights, we can easily use formulas (17) and (18) to estimate a mutual fund’s security selection and market timing in a given month. This enables us to evaluate a manager’s historical track record. Until now we have not mentioned anything about the cost of benchmarking. Sharpe (1992) argues that an adequate benchmark should be low in cost. Except for the bills and bonds, the indices we have used are not tradable, meaning that we will have to make a well educated guess of what it would cost to replicate them. In a paper from 2000, Ibbotson and Kaplan use RBSA to estimate the policy weights of mutual funds. In this matter, they assume that the cost of the benchmark is 2 basis points a month, which yields a cost of approximately 25 bps annually. This seems to be a reasonable level, and is also assumed in this analysis.

Fig. 9 shows the graphical development of DnB Norge (I)'s cumulative excess return, security selection and market timing from Jan. 2006 to Dec. 2010.³² The figures are net the cost of the style-benchmark. We also include the fund's cumulative return in excess of OSEFX.

FIGURE 9:

Cumulative Excess Return, Security Selection and Market Timing
and the Fund's Return in Excess of OSEFX.
Fund: DnB Nor Norge (I). Period: Jan. 2006 - Dec. 2010



Descriptive statistics using monthly returns

Fund: DnB Nor Norge (I). Period: Jan. 2006 - Dec. 2010

	Excess Return	Security Selection	Market Timing	Fund's Return in Excess of OSEFX
Average (monthly)	0,06 %	0,40 %	-0,34 %	0,12 %
StdDev	1,81 %	1,20 %	1,54 %	1,22 %
t-statistic	0,25	2,57 *	-1,72	0,75

** Significant at a 1 % level

* Significant at a 5 % level

On average, DnB Nor Norge (I) outperformed the style-benchmark by 6 basis points per month, which amounts to approximately 0.72% per annum. The t-statistic associated with the mean is however, not statistically significantly different from zero at any reasonable level.

³² No compounding is done in Figure 9 (and the subsequent ones using similar portrayals). This makes it possible to compare vertical distances directly at any point in the figure. The average values in Figure 9 are calculated using geometric averages. More specifically, the geometric mean, $\mu_g = [\prod_{i=1}^n (1 + r_i)]^{1/n} - 1$, where r_i = return under study, and n = length of time-series. Geometric standard deviation, $\sigma_g = \exp\left(\sqrt{\frac{\sum_{i=1}^n (\ln(1+r_i) - \ln(\mu_g+1))^2}{n}}\right) - 1$. Here: $n = 60$

Furthermore, we see that DnB Nor Norge (I) possess skills (or luck) within security selection (average is positive and statistically different from 0), but loses by trying to time the market (although not significantly different from 0).

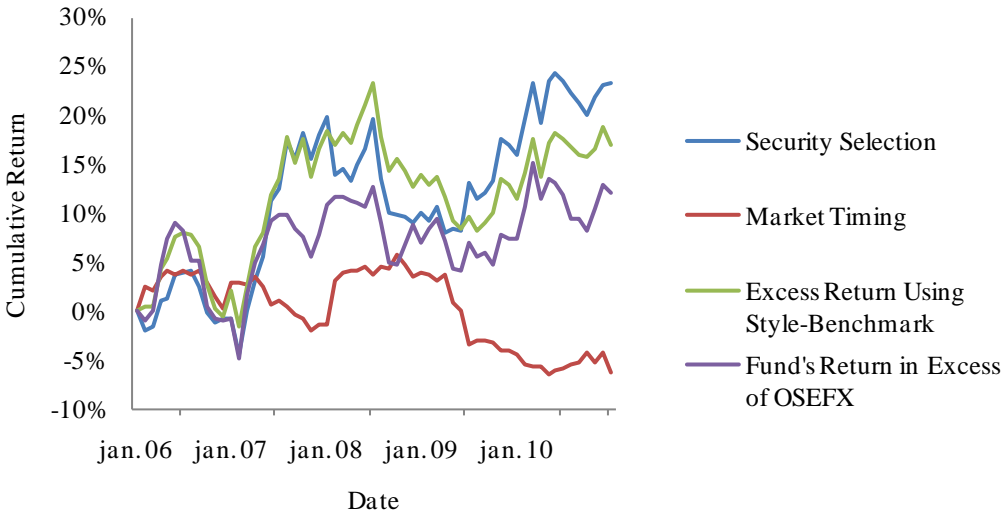
Previously we argued that OSEFX is not a suitable benchmark for DnB Nor Norge (I), since OSEFX is not able to mimic the fund's long-term investment policy. Figure 9 shows that OSEFX has a smaller long-term risk than the fund, since the benchmark overestimates the fund's performance compared to our risk-adjusted performance measurement. Thus, if OSEFX were used as a benchmark for DnB Nor Norge (I),³³ the managers would just need to cease using market timing and security selection in order to "beat the benchmark". Clearly, this would give a wrong impression of the manager's historic track record, since the return in excess of the OSEFX would just be the compensation for extra risk in the mutual fund. This is not something investors should pay management fees for.

³³ DnB Nor Norge (I) use the Linked OSEBX as their benchmark

Let us now look at Alfred Berg Gambak’s performance the last 5 years:

FIGURE 10:

Cumulative Excess Return, Security Selection and Market Timing
and the Fund’s Return in Excess of OSEFX.
Fund: Alfred Berg Gambak. Period: Jan. 2006 - Dec. 2010



Descriptive statistics using monthly returns

Fund: Alfred Berg Gambak. Period: Jan. 2006 - Dec. 2010

	Excess Return using Style	Security Selection	Market Timing	Fund's Return in Excess of OSEFX
Average	0,24 %	0,35 %	-0,11 %	0,17 %
StdDev	2,38 %	2,57 %	1,22 %	2,36 %
t-statistic	0,79	1,07	-0,71	0,57

** Significant at a 1 % level

* Significant at a 5 % level

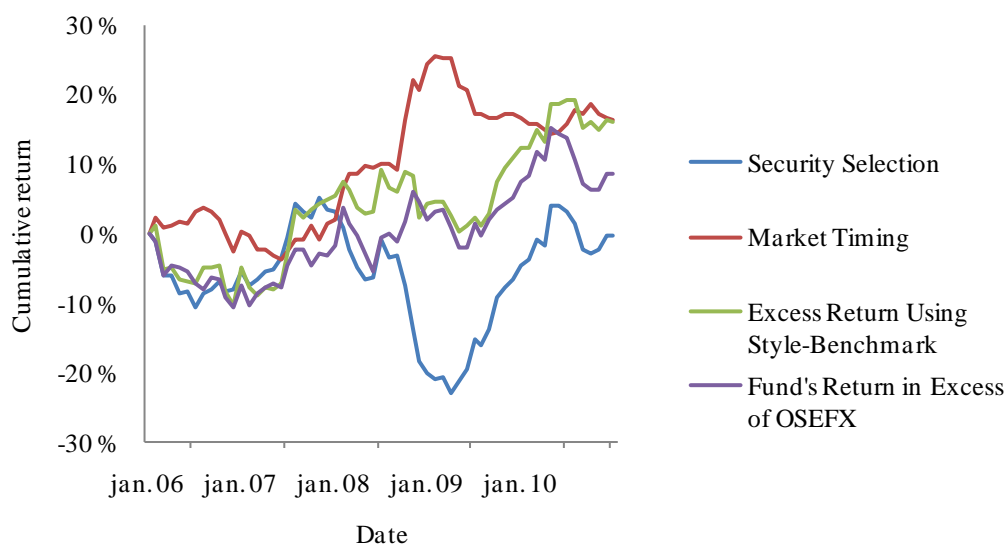
Previously, we have not been able to conclude whether Alfred Berg Gambak utilizes market timing. Figure 10 shows that the average market timing is only -0.11% per month from 2006 to 2010, and is not significantly different from 0%. Moreover, the fund has positive average excess return and security selection, but none of these are significantly different from 0%.

Just as for DnB Nor Norge (I), we argued that OSEFX is not suitable as a benchmark for Alfred Berg Gambak. However, unlike the case with DnB Nor Norge (I), we see that OSEFX as a benchmark underestimates Alfred Berg Gambak’s performance compared to our risk-adjusted performance measurement. Therefore it should be in the fund’s interest not to use OSEFX as a benchmark, since the long-term risk is seemingly less than that of OSEFX. Interestingly, the fund uses OSEFX as their benchmark (Alfred Berg Fondsforvaltning).

Let us look at another example that shows the how well the model captures changes. On December 1st 2007, the fund Delphi Norge got a new portfolio manager. Figure 11 shows how this affected the managerial performance:

FIGURE 11:

Cumulative Excess Return, Security Selection and Market Timing
and the Fund's Return in Excess of OSEFX.
Fund: Delphi Norge. Period: Jan. 2006 - Dec. 2010

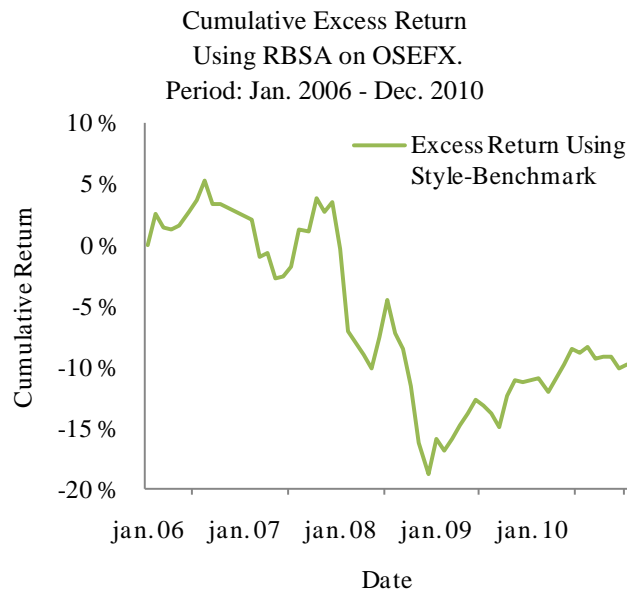


The figure shows that the fund's managerial performance shifts during January 2008. The new manager seems to be good at timing at market, but not so good at picking stocks.³⁴ Hence, our model seems to be good at capturing mutual fund events. In Chapter 2, we will use this framework to see whether a change in a fund's management causes a change in excess return, security selection or market timing.

Our framework is based on the passive return-series of 10 predefined asset classes (cf. Table 5, pg. 21). As a test of whether these indices are suitable, it would be interesting to look at the cumulative performance of OSEFX. If we have picked suitable indices, the average sum of market timing and security selection should be close to 0% per month. Of course, it does not make sense to look at market timing and security selection in an index; therefore we are only interested in the excess return. Figure 12 shows the cumulative performance of OSEFX over the years 2006 to 2010:

³⁴ The average monthly security selection and market timing after January 2008 are significantly different from those before January 2008. In Chapter 2, we will look into how we can measure this

FIGURE 12:



Descriptive statistics using monthly returns:

	Excess Return
Average (monthly)	-0,18 %
StdDev	1,89 %
t-statistic	-0,75

** Significant at a 1 % level

* Significant at a 5 % level

Ideally the average excess return should be close to 0%. In this case we see that it is approximately -0.2% per month, although not significantly different from 0. Interestingly, it seems like the indices do not work too well during the financial crisis. When we add the fact that $R_{QP}^2 \approx 94\%$ (on January 31st 2011, cf. Figure 5, pg. 48), we conclude that the 10 indices are suitable.

1.6.5. Section Summary

In this section, we have illustrated how we can use the actual style-weights and the policy style-weights to estimate a mutual fund's excess return. Furthermore, we have split this into security selection and market timing, and seen how their cumulative returns evolve over time. As these examples show, a remarkable amount of information can be revealed from an analysis of the returns provided by the mutual fund.

1.7. Weaknesses in Framework and Future Research

One of the weaknesses with this framework is that the estimated policy weights change over time, despite policy weights are constant. We argue that since the policy style-weights do not change much over time, this should not pose a large problem. Nevertheless, this shows the problems with balancing between practical models and having models which are true to theory.

Several of the indices used in this framework have weaknesses such as e.g., high correlation and being non-tradable. An investor with more experience in the financial market is likely to find more appropriate indices.

Throughout this chapter, we have used monthly return-data. Sharpe (1995) argues that the use of monthly data is best because that is what is most readily available. Moreover, he argues, the problem with using daily returns is that one will get more noise in the data. For future research, it would be interesting to see whether weekly return-data are better in capturing the fund's short-term movements.

1.8. Conclusion

The purpose of this chapter was to develop a framework that can easily be used by investors to estimate a mutual fund's actual weights and policy weights in a set of asset classes, and to estimate a mutual fund's security selection and market timing.

We start the chapter by generalizing Brinson, Hood and Beebower's framework (BHB, 1986). Doing so, we see that we can measure a mutual fund's security selection and market timing only if we have the fund's actual and policy weights. Unless we are lucky to get these weights directly from the fund, we suggest that the weights can be estimated by Return Based Style Analysis (Sharpe, 1992).

In RBSA, the weights no longer represent a fund's historical proportions in a set of asset classes, but weights that reflect the behavior of the fund. We assume that weights that reflect the fund's short-term and long-term behavior are good estimates of a fund's actual and policy weights respectively. In order to estimate a fund's policy weights, we suggest using RBSA with 120 months of return-data. To estimate a fund's actual weights, we argue that we need to balance between having small enough time-series to capture the fund's short term movements, but long enough time-series to avoid excessive noise.

The framework illustrates that the length of the return-series has an effect on the interpretation of the style-weights, which in turn affects the interpretation of what the difference between a fund's return and the asset class portfolio series is. Sharpe uses 60 months with return-data to estimate a fund's actual weights. We warn against this, and suggest using the stepwise approach as described in subsection 1.5.2. to find the optimal length of the return-series. In this matter, we find that 24 months with return-data is enough to estimate an average Norwegian mutual fund's actual weights. Once we have estimated the actual and policy weights, we can use them in the generalized BHB-framework to estimate a mutual fund's security selection and market timing. To my knowledge, this chapter is the first formalization of the links between the papers of BHB and Sharpe.

The return associated to the asset allocation is the investor's responsibility and not the manager's, since the investor chooses to bet on that particular risk. In this matter it is essential for investors to have an overview of the fund's determinants of risk. Our framework gives an

investor the possibility to access a mutual fund's short- and long-term risk; making it easier for them to choose mutual funds that suit their risk-preference.

If we do not have a benchmark that accounts for a fund's true long-term risk, we might up end up paying too much in management fees, because we falsely believe that the return which is created in excess of the benchmark is security selection and/or market timing, while in reality it is just the payoff from extra risk in the mutual fund. Our framework accounts for the fund's long-term risk, enabling investors to easily get an overview of the fund's managerial performance.

CHAPTER 2:

An Empirical Study of Norwegian Mutual Fund Managers

– Using the Two-Step Return Based Style Analysis

2.1. Introduction

This chapter builds on the framework that is developed in chapter 1, and the two chapters must therefore be read in a sequential order. We use the framework to study three important questions related to Norwegian mutual fund managers:

- 1) How much of the total variation in mutual fund return is explained by asset allocation, security selection and market timing respectively?
- 2) Is the average managerial performance positive?
- 3) *Ceteris paribus*, does a change in a mutual fund's management cause a change in managerial performance?

Before we start the analysis, we will have a closer look at the objective of each problem statement and present some previous studies that have addressed the same questions before.

2.1.1. Problem Statement 1:

The objective of problem statement 1 is to analyze the relative importance of asset allocation, security selection and market timing on a mutual fund's variability over time. As discussed in Chapter 1, the return associated to the asset allocation is the investor's responsibility and not the manager's, since the investor chooses to bet on that particular risk. On the other hand, the manager is responsible for security selection and market timing. This implies that variability of asset allocation is the investor's responsibility, whereas the variability in security selection and market timing is the manager's responsibility. In this matter, our results will shed light on

whether it is the manager or the investor that are responsible for most of the fund’s variability and return over time.

No studies have used Norwegian mutual fund data to study similar problems. However, numerous studies have used U.S. data to study the question. Brinson, Hood and Beebower’s (hereafter BHB) paper “Determinants of Portfolio Performance” (1986) is the first study of this kind. Using the framework we described in Chapter 1 (cf. subsection 1.2.), BHB study the variability of each quadrant over time. Their analysis is based on return-data of 91 large U.S. pension plans from 1974 to 1983. Another well-known study is by Brinson, Singer and Beebower (hereafter BSB) in “Determinants of Portfolio Performance II: An Update” (1991). Their analysis is based on BHB’s framework, and uses return-data of 82 large U.S. pension plans from 1977 to 1987. Table 9 shows the results of the two analyses:

TABLE 9:

Average Percentage of Variation in Return Explained by Each Quadrant

		BHB (1986)		BSB (1991)	
		Selection		Selection	
		Actual	Passive	Actual	Passive
Timing	Actual	(IV) Average: 100%	(II) Average: 95.3%	(IV) Average: 100%	(II) Average: 93.3%
	Passive	(III) Average: 97.8%	(I) Average: 93.6%	(III) Average: 96.1%	(I) Average: 91.5%

The studies show that asset allocation (i.e., Quadrant I) accounts for most of a fund’s variation in return over time, whereas security selection and market timing in sum account for less than 10% of the fund’s variation in return over time. This means that the investors have the largest responsibility for a fund’s variability over time, not the manager. The subsequent implication of this is that the investor has the largest responsibility for the fund’s return, since it is the investor who chooses to bet on the risk that follows with the fund’s asset allocation.

2.1.2. Problem Statement 2

A fund's managerial performance is determined by security selection and market timing; which in sum constitute the fund's excess return. By studying the average excess return in Norway, we will find out whether active management has been valuable for Norwegian investors. By studying the average security selection, we will be able to say something about the efficiency of the Norwegian equity market. Moreover, by studying the average market timing in Norway, we might also be able to tell whether the assumptions of Mossin (1968), Merton (1969, 1971) and Samuelson (1969) are too strict (cf. main introduction).

Problem statement 2 has been subject to an abundant amount of studies using U.S. data. However, Norwegian mutual fund managers and their performance have been subject to very little research. One early paper is by Gjerde and Sættem (1991). They find that Norwegian mutual fund managers possess market timing abilities, but have less ability to pick stocks. Overall, they find that the mutual funds outperform the market during 1982 – 1984, but underperform from 1984-1990. Then there is a gap in the Norwegian research until Sørensen (2009). He uses the Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965) and Mossin (1966) with OSEFX as a benchmark, the Fama-French (1993) three-factor model and the Fama-French-Carhart (1997) four-factor model³⁵ on a dataset from 1982 to 2008 without survivorship-bias. Doing so, he finds little evidence of abnormal return.

The RBSA-methodology has never been used to investigate the managerial performance of Norwegian mutual funds. Unlike the factor-models which are mentioned above, the two-step RBSA acknowledges OSEFX may not be the best way of capturing a fund's long-term risk. Moreover, the two-step RBSA is not a static model that says that small-caps is always better than growth-stock, or that value stocks is always better than growth stocks. However, the framework acknowledges that there are monthly differences in the 10 indices.

2.1.3. Problem Statement 3

The market has a tendency to penalize poorly performing funds via a systematic loss in market share to superior performers (Ippolito, 1992). In this matter, a mutual fund's board and investment advisors have a strong interest in making sure that the mutual fund manager

³⁵ The four-factor model accounts the following 4 factors: market risk premium, SMB (the difference between small and large caps stocks), HML (the difference between value and growth stocks) and momentum

provides satisfactory results. In cases where the board and investment advisors are unsatisfied with the manager, a natural consequence is to dismiss the manager. By analyzing the consequences of fund manager replacement on a fund's subsequent excess return, we will shed light on whether internal control mechanisms are effective in reversing the performance of poorly performing mutual funds. Understanding the post-replacement effects in a mutual fund setting is especially useful for the fund's investors. There are two reasons for this: 1) it enables them to know whether the fund's board and investment advisors engage in value-enhancing activities and 2) it shows the effect of the consequences on the mutual fund's return.

Few international studies address problem statement 3. However, one exception is Khorana (1996 and 2001). Khorana (1996) studies the relationship between managerial replacement and pre-replacement performance. In this matter, he finds evidence supporting the presence of an inverse relationship between the probability of fund manager replacement and past performance.

In a newer study, Khorana (2001) finds that the replacement of poorly performing managers leads to substantial improvements in post-replacement performance relative to the pre-replacement performance. Moreover, he finds that the new fund managers continue to exhibit underperformance in the post-replacement period. This, Khorana's results show that the internal market for corporate control in the mutual fund industry is effective in disciplining poorly performing fund managers. By hiring new managers, the fund's board and investment advisors are able to reverse the fund's performance to more normal levels. On the other hand, his data show that the samples of mutual funds that overperform in the pre-replacement period experience a significant deterioration in post-replacement performance. The new managers continue to overperform, but without significant superior performance.

Khorana's analysis is based on using the CAPM and the Fama-French-Carhart (1997) four-factor model as frame of reference to measure abnormal return. No similar analysis has been made with RBSA before, and neither has it been done with Norwegian mutual fund data. Moreover, it would be interesting to analyze the consequences of the replacement on the fund's subsequent return from security selection and market timing. This would enable us to see whether it is security selection or market timing that distinguishes a good manager from a poor manager. To my knowledge, this has not been analyzed before.

2.1.4. Disposal

The remainder of the paper is organized as follows. Section 2.2 describes the methodology and datasets that are used for each problem statement. Section 2.3 provides a discussion of the empirical results. In section 2.4, we look at the studies' weaknesses, whereas we conclude in section 2.5.

2.2. Methodology and Data

All analysis related to our 3 problem statements are based on the framework developed in Chapter 1. In this matter, we use the same 10 asset classes as before: bills, government bonds (3 years and 10 years), Norwegian equities (small-caps, mid-caps growth, mid-caps value, large-caps growth and large-caps value), European equities (excluding Norwegian equities), and world equities (excluding European equities). For an overview of their associated passive-return series, see Table 5 in Chapter 1. These time-series are collected via DataStream.

All problem statements are related to current, active Norwegian mutual funds that focus on Norwegian equity. In order to use the framework in Chapter 1, we restrict ourselves to only look at mutual funds that have long positions in the asset classes. In Chapter 1, we argue that we need 10 years with return-data to estimate a fund's policy weights. Based on all these prerequisites, we can potentially analyze 46 mutual funds. A list of these is given in Appendix D. Using a unit-root test; we find that all these mutual funds have stationary return-series (see appendix E).

We use a fund's net asset value (NAV) to compute mutual fund returns. NAV is the fund price excluding redemption fees, sales charges and front/back end load. It is gross taxes, and net of management fees and costs. Furthermore, it assumes that dividends are reinvested in the fund. We calculate the return from period $T-1$ to T as follows:

$$\tilde{R}_{T-1,T} = \frac{NAV_T}{NAV_{T-1}} - 1$$

The time-series are collected via Børsprosjektet NHH and Bloomberg.³⁶

In the following subsections, we will look more specifically into the methodology and datasets that are used in the analysis related to each problem statement.

³⁶ Courtesy of Petter Slyngstadli in Holberg Forvalting

2.2.1. Methodology and Data in Problem Statement 1

In Chapter 1, we find that we only need to quantify Quadrant IV, II and I to measure the return-effect of a mutual fund's security selection and market timing. Similarly, we only need to measure the amount of variation that is explained by Quadrant IV, II and I in order to calculate how much of the total variation in mutual fund return that is explained by asset allocation, security selection and market timing. Recall from Chapter 1 that the efficacy of the asset classes can be measured by the portion of the variance of a mutual fund's return that is explained by the predefined asset classes (same as equation 13):

$$R_{QP}^2 = \frac{S_r^2 - s^2}{S_r^2} = 1 - \frac{s^2}{S_r^2}$$

where S_r^2 = sample variance of mutual fund m and s^2 = sample variance of the tracking error (cf. problem (9), pg. 30).

Quantifying the amount of variation that is explained by Quadrant IV is easy. By definition it is 100%. Quantifying the amount of variation that is explained by Quadrant II and I will require some more work. Recall that Quadrant II is measured by the fund's actual weights and the passive return of the predefined asset classes, whereas Quadrant I is measured by the fund's policy weights and the passive return of the predefined asset classes. By using RBSA with 24 months of return-data, we can use equation (13) to estimate how much of the total variation in a fund's return that is explained by Quadrant II. Similarly, by using 120 months with return-data, we can use equation (13) to estimate how much of total variation in a fund's return that is explained by equation Quadrant I.³⁷ Once we have done this for each fund, we calculate the arithmetic average R_{QP}^2 for all mutual funds in Quadrant I and Quadrant II. This will in enable us to measure the average amount of variation that is explained by asset allocation, security selection and market timing for all funds.

This analysis is based on the 46 mutual funds that are specified in Appendix D. To estimate their policy weights, we use monthly return-data from Jan. 31st 2001 to December 31st 2010. To estimate the actual weights, we use monthly return-data from Jan. 31st 2009 to December 31st 2010.

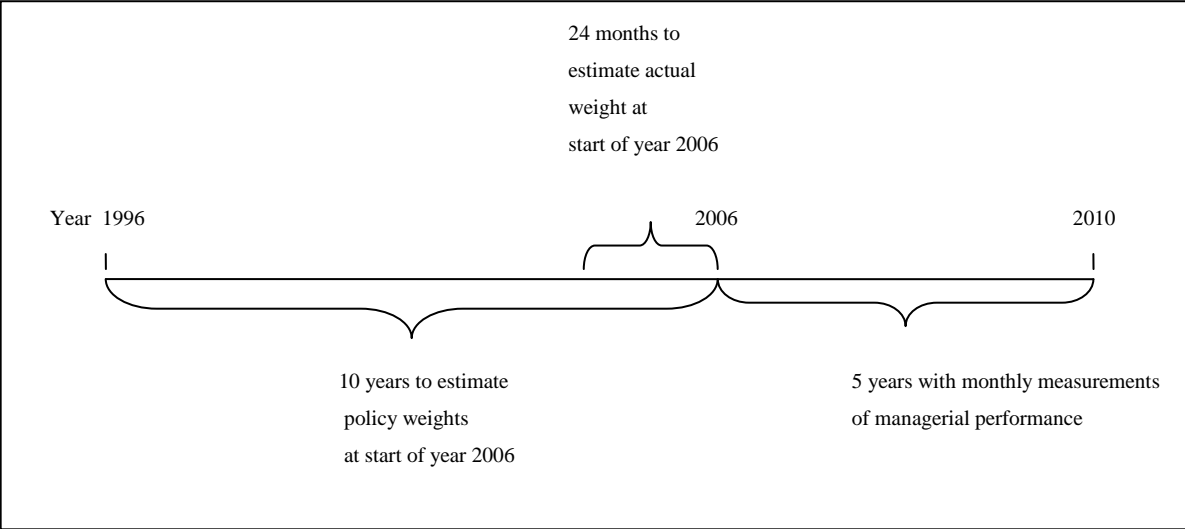
³⁷ We use A. Steiner's coding (available through the MATLAB central) to estimate the actual and policy weights. He uses a definition of R_{QP}^2 that is different from ours. Due to this, we have changed his coding so that we can measure it according to our definition in equation (13)

2.2.2. Methodology and Data in Problem Statement 2

In order to investigate the average managerial performance of Norwegian mutual funds, we use the framework in chapter 1 to estimate each fund’s excess return, security selection and market timing in each month from 2006 to 2010. Figure 13 illustrates this:

FIGURE 13:

Methodology for calculating each fund’s managerial performance



For illustrational purposes, Figure 13 only shows that we estimate the actual and policy weights for January 31st 2006. However, as in Chapter 1 (subsection 1.6.3.), we use rolling style decomposition to estimate the actual and policy weights for each month in the period 2006 to 2010, before we use these in formula (17) and (18) to estimate the fund’s managerial performance in each month over the same period.

Once we have estimated each fund’s monthly excess return, security selection and market timing, we calculate the fund’s geometric average monthly excess return, security selection and market timing. When we have done this for each mutual fund under study, we proxy the average managerial performance of Norwegian mutual funds by calculating the arithmetic average monthly excess return, security selection and market timing for all funds.

Since RBSA requires 10 years of return-data to estimate the funds’ policy weights, and we study the fund’s monthly managerial performance from 2006 to 2010, the analysis requires mutual funds with at least 15 years with return-data. Out of the 46 funds in appendix D, 22

mutual funds these fulfill this requirement. See appendix F for the list of which mutual funds are used for this analysis.

2.2.3. Methodology and Data in Problem Statement 3

From Khorana (1996), we know that the replacement of underperforming managers is likely to occur due to dismissal. The replacement of an average manager can be due to either voluntary replacement or dismissal. Moreover, managerial replacement of overperforming managers is likely to come voluntary. Even though voluntary departure and dismissal will be reflected in managerial turnover, the factors leading to replacement are different in the two cases. Unfortunately, the lack of any publicly available information makes us unable to distinguish explicitly among the various reasons for replacement (Khorana, 2001). As a proxy for the reason behind replacement, we do as Khorana and decompose the sample of mutual funds based on the pre-replacement performance.

We measure the pre-replacement performance by the arithmetic average monthly excess return. We define managers that have negative arithmetic average monthly excess return in the pre-replacement period as underperformers, and define managers that have positive arithmetic average monthly excess return in the pre-replacement period as overperformers. In the absence of publicly available information on the rationale behind replacement, a decomposition like this serves as the second best alternative.

This problem statement requires information on when the mutual funds changed management. The information of the month and the year of managerial replacement are obtained from Morningstar.³⁸

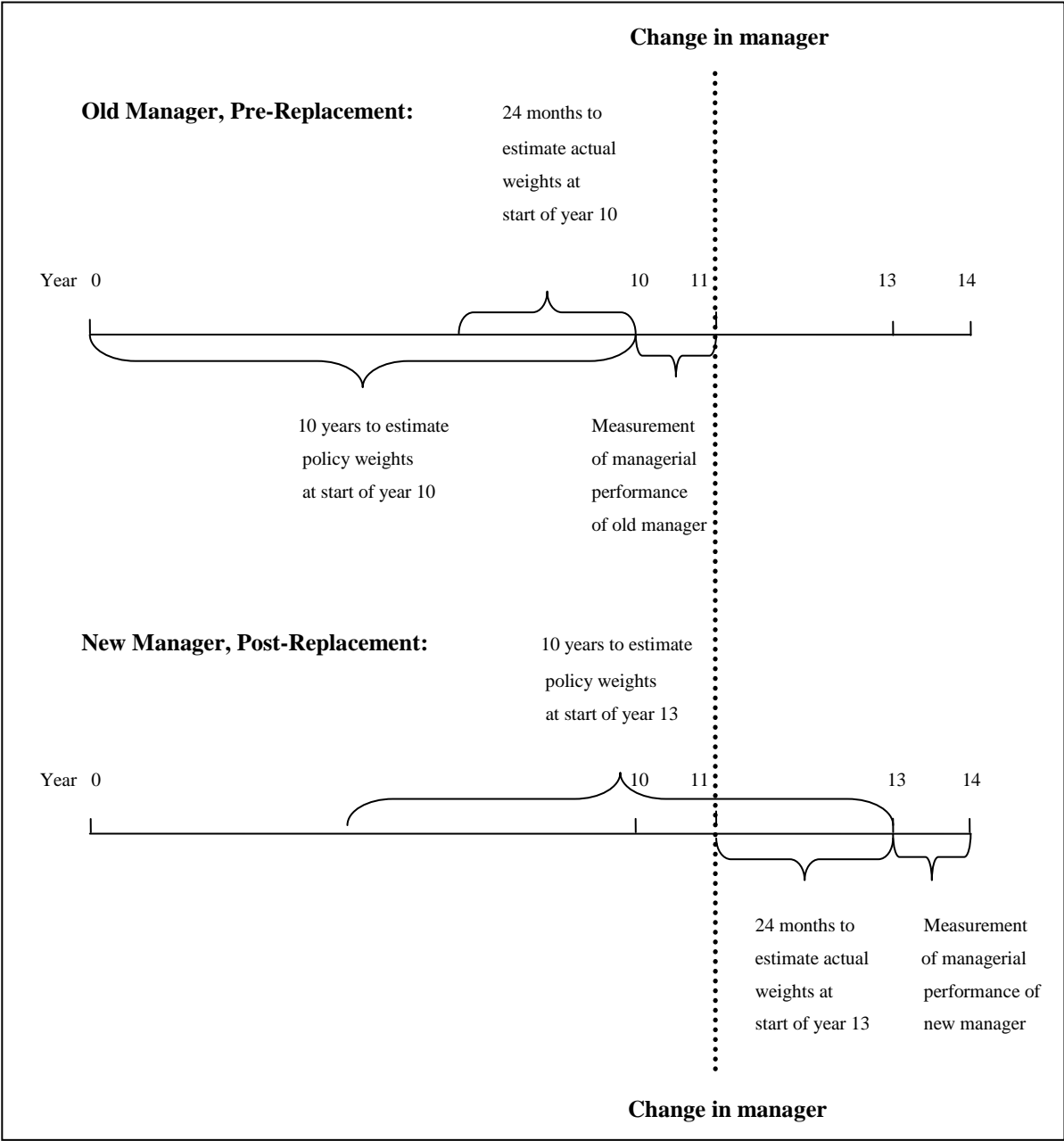
Our analysis is based on all Norwegian mutual funds that have 11 years with return-data pre-replacement. We use the first 10 years to estimate the policy weights for the first month in the 11th year, and use the 11th year to study the managerial performance of the old manager. We ensure that the new manager gets 3 years with return-data post-replacement. The 2 first years are used for estimating the new manager's actual weights in the first month of the 13th year, whereas the last year is used to study the new manager's managerial performance. Based on these prerequisites, we can analyze 14 current mutual funds. Out of these funds, 7 mutual

³⁸ Note that Morningstar only publishes the last change in mutual fund management

funds underperformed pre-replacement and 7 funds overperformed pre-replacement. See appendix G for a list of which mutual funds are analyzed, and when managerial replacement took place. Figure 14 illustrates this methodology.

FIGURE 14:

Methodology for Problem Statement 3:



For illustrational purposes, Figure 14 only shows that we estimate the actual and policy weights at the start of year 10 for the old manager and at the start of year 13 for the new manager. However, as in Chapter 1 (subsection 1.6.3.), we use rolling style decomposition to

estimate the actual and policy weights for each month in the years 10 – 11 and 13 – 14. These weights are in turn used in equation (17) and (18) to measure each fund’s excess return, security selection and market timing in each month. Since our main interest is in whether the changes are significant, we chose not to include the cost of benchmarking when we calculate each fund’s managerial performance. Once the managerial performance has been calculated, we calculate each fund’s geometric average monthly excess return, security selection and market timing, both in the pre-replacement period (year 10-11) and the post-replacement period (year 13-14). When we have done this for each mutual fund under study, we proxy the average managerial performance pre-replacement for the underperformers and the overperformers by calculating the arithmetic average monthly excess return, security selection and market timing across the 7 overperformers and the 7 underperformers respectively. The same method is used to proxy the average managerial performance post-replacement across the respective 7 overperformers and the 7 underperformers. We can compare the mean performance in the pre- and post-replacement periods using the following t-statistic:

$$t = \frac{(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)}{\sqrt{\left(\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}\right)}}$$

This is approximately t-distributed with $\nu = \frac{\left(\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}\right)^2}{\frac{S_1^2}{(n_1-1)} + \frac{S_2^2}{(n_2-1)}}$ degrees of freedom (Keller, 2005).

where:

\bar{x}_1	=	Average performance in either excess return, security selection or market timing, pre-replacement
S_1^2	=	Sample variance in either excess return, security selection or market timing, pre-replacement
\bar{x}_2	=	Average performance in either excess return, security selection or market timing, post-replacement
S_2^2	=	Sample variance in either excess return, security selection or market timing, post-replacement
n_1	=	Total number of mutual funds pre-replacement
n_2	=	Total number of mutual funds post-replacement

In this case, $n_1 = n_2 = 7$. Our null-hypothesis (for both underperformers and overperformers) is that the respective average performance in excess return, security selection and market timing does not change after the managerial replacement. Hence, $H_0 : \mu_1 - \mu_2 = 0$.

2.3. Results and Analysis

2.3.1. Problem Statement 1

In this subsection we will look at the empirical results related to the question of how much of the total variation in mutual fund return is explained by asset allocation, security selection and market timing respectively. Table 10 shows the arithmetic average and median amount of total variation in mutual fund return that is explained by Quadrant IV, II and I:

TABLE 10:

		Selection	
		Actual	Passive
Timing	Actual	(IV) Average: 100% Median: 100%	(II) Average: 95.1% Median: 97.3%
	Passive	(III) N/A	(I) Average: 90.6% Median: 92.2%

The total amount of variation in mutual fund return that is explained by security selection is on average 4.9% (Quadrant IV – Quadrant II), whereas market timing explains 4.5% of the variation on average (Quadrant II – Quadrant I). The amount of variation in mutual fund return that is explained by asset allocation is on average 90.6%. Unlike BHB (1986) or BSB (1991), we do not have access to the funds’ actual weights. We have estimated the values by the two-step RBSA. In this matter, the similarity of our results to those of BHB and BSB confirm the reliability of the framework in chapter 1.

Our results clearly show that it is the investor who has the largest responsibility for the fund’s variability in return; not the manger. The implication of this is that it is the investor who has the largest responsibility of the fund’s return over time, since they choose to bet on the risk that follows with the fund’s asset allocation. Of course, this is under the assumption that the investor is fully aware of the fund’s asset allocation and the subsequent long-term risk when they invest in the mutual fund. The average Norwegian mutual fund investor should therefore use more time on reviewing their fund’s asset allocation and less time on manager searches.

2.3.2. Problem Statement 2

In this subsection we will look at the empirical results related to whether Norwegian mutual fund managers are to create positive managerial performance. Recall that managerial performance is the same as excess return, which we can split into security selection and market timing. Ignoring any costs associated with style-benchmarks, we get the descriptive statistics given by table 11:

TABLE 11:

Arithmetic average monthly excess return, security selection and market timing, and the associated standard deviation and t-statistic when cost of benchmarking is excluded.³⁹ Period: 2006-2010

	Excess Return	Security Selection	Market Timing
Average (monthly)	-0.005 %	0.175 %	-0.180 %
Stdev (monthly)	0.173 %	0.251 %	0.180 %
t-statistic	-0.13	3.28 **	-4.70 **

** Significant at 1% level

* Significant at 5% level

For an overview of the geometric average monthly excess return, security selection and market timing for each fund under study, see Appendix H. The analysis shows that the 22 current Norwegian mutual funds are good in picking stocks, but poor in timing the market. Both monthly security selection and monthly market timing are significant at 1% significance level. In sum, the mutual funds underperform the style-benchmark. However, the sum of security selection and market timing is close to zero, and not significantly different from 0%. This result is in accordance with Sørensen's result.

The above results are under the unlikely assumption that the benchmark has zero cost. Adding a cost of 2 basis points per month (cf. subsection 1.6.4.), we get the descriptive statistics given by Table 12:

³⁹ The t-statistics in this table (and subsequent ones using similar portrayals) is calculated as follows: $\frac{\bar{R}-0}{\frac{S}{\sqrt{n}}}$, where \bar{R} = sample mean of managerial performance (either excess return, security selection or market timing) and S = sample standard deviation of managerial performance. n = sample size. The critical value of a two-sided test is found using $n - 1$ degrees of freedom in the student t-distribution

TABLE 12:

Arithmetic average monthly excess return, security selection and market timing, and the associated standard deviation and t-statistic when cost of benchmarking is included. Period: 2006-2010

	Excess Return	Security Selection	Market Timing
Average (monthly)	0.015 %	0.195 %	-0.180 %
Stdev (monthly)	0.173 %	0.251 %	0.180 %
t-statistic	0.41	3.65 **	-4.70 **

** Significant at 1% level

* Significant at 5% level

Now the average excess return is positive, and annualizes to approximately 18 basis points. However, the figure is still not significantly different from 0. Note that market timing is unaffected by the change. The reason for this is that the inclusion of the cost makes the fund's return increase without changing the estimated actual or policy weights.

The significance of the security selection seems to point in the direction that the mutual funds have either skills or information. The implication of this is that the Norwegian equity market cannot be efficient in the semi-strong form.

If the mutual funds had stopped timing the market, the excess return would have increased to approximately 2.4% a year. Hence, the strategic under- or overweighting of an asset class relative to its policy weights leads to worse results. This is in line with the theories by Mossin (1968), Merton (1969, 1971) and Samuelson (1969) (cf. part 1). However, it does not imply that MMS's assumptions are correct.

Only one of the 22 mutual funds under study manages to have positive market timing and security selection at the same time, even when accounting for the cost of the benchmark.⁴⁰ The fact that few funds have the ability to select undervalued securities and time the market at the same time is in line previous research. See e.g., Volkman (1999).

2.3.3. Problem Statement 3

In this subsection, we will look at the empirical results related to whether a change in a mutual fund's management causes a change in managerial performance. The 7 underperformers have the following descriptive statistics pre-replacement:

⁴⁰ This is Storebrand Vekst

TABLE 13:

Arithmetic average monthly excess return, security selection and market timing, and the associated standard deviation and t-statistic for underperformers pre-replacement

	Excess Return	Security Selection	Market Timing
Average (monthly)	-0.275 %	0.144 %	-0.430 %
Stdev (monthly)	0.378 %	0.666 %	0.336 %
t-statistic	-1.92	0.57	-3.39 *

** Significant at a 1 % level

* Significant at a 5 % level

The fact that the underperformers have negative average excess return should not come as a surprise, cf. how we defined underperformers. However, we note that the excess return is not different from 0% at any reasonable significance level. We observe that underperformers are characterized by significant negative market timing, and insignificant security selection.

The replacement of underperforming managers is likely to occur due to dismissal. In this matter, it is interesting to look at the funds' performance in the post-replacement period:

TABLE 14:

Arithmetic average monthly excess return, security selection and market timing, and the associated standard deviation and t-statistic for underperformers post-replacement

	Excess Return	Security Selection	Market Timing
Average (monthly)	0.559 %	0.443 %	0.114 %
Stdev (monthly)	0.587 %	0.815 %	0.300 %
t-statistic	2.52 *	1.44	1.00

** Significant at a 1 % level

* Significant at a 5 % level

After the managerial replacement, the funds experience a dramatic increase in average excess return. Now the average excess return is positive and significant at 5% level, and amounts to above 6.7% per annum. We note that average market timing is not significantly different from 0% anymore. The question is then: which changes are significant? We get the t-statistics in table 15:

TABLE 15:

Testing for differences in average monthly managerial performance before and after replacement of underperforming manager

	Excess Return	Security Selection	Market Timing
t-statistic	3.16 *	0.75	3.20 *

** Significant at a 1 % level

* Significant at a 5 % level

When the samples have negative average excess return in the pre-replacement period, we see that the managerial replacement significantly increases average excess return in the post-replacement period. We mentioned that managerial replacement of underperforming managers is likely to be due to dismissal. If poor fund performance is attributable to managerial abilities rather than bad luck, and if the fund's board and investment advisors are on average able to attract an average managerial talent, one would indeed anticipate the managerial change to cause an improvement in the average excess return. This implies that market for corporate control in the Norwegian mutual fund industry is effective in disciplining poorly performing fund managers.

Khorana (2001) finds that when underperformers are replaced, the new managers continue to underperform in the post-replacement period. Our findings show that the new managers overperform in the post-replacement period. However, due to the low sample size of our analysis, we should be careful with interpreting the absolute numbers too much. We should rather have an emphasis on whether the changes and figures are significant or not. Here we find that the change is positive and significant; which is in line with theory. Moreover, we find that the change mainly comes because the new manager utilizes less market timing. Assuming that fund's board and investment advisors are able to attract an average managerial talent, Table 14 implies that average managers avoid market timing, and do not possess stock-picking skills.

Let us look at the descriptive statistics of the managers that performed well in the pre-replacement period:

TABLE 16:

Arithmetic average monthly excess return, security selection and market timing, and the associated standard deviation and t-statistic for overperformers pre-replacement

	Excess Return	Security Selection	Market Timing
Average (monthly)	0.535 %	0.509 %	0.028 %
Stdev (monthly)	0.483 %	0.291 %	0.498 %
t-statistic	2.93 *	4.63 **	0.15

** Significant at a 1 % level

* Significant at a 5 % level

We see that these managers are able to beat the style-benchmark with above 6.4% per annum. Most of this is due to significant security selection. Furthermore, we see that market timing is not significantly different from 0%. Hence, overperformers are characterized by stock-picking skills and avoidance of market timing. Recall that managerial replacement of overperforming managers is likely to come voluntary. It would be interesting to see what effect this has on the post-replacement performance:

TABLE 17:

Arithmetic average monthly excess return, security selection and market timing, and the associated standard deviation and t-statistic for overperformers post-replacement

	Excess Return	Security Selection	Market Timing
Average (monthly)	0.214 %	0.397 %	-0.191 %
Stdev (monthly)	0.351 %	0.312 %	0.280 %
t-statistic	1.61	3.37 *	-1.81

** Significant at a 1 % level

* Significant at a 5 % level

Now we see that security selection has decreased, but it is still significantly different from 0% at 5% level. We see that market timing has become negative, but it remains insignificant. In total, the excess return is still positive, but not significantly different from 0%. The question is then: are these changes significant? Table 18 tells the story:

TABLE 18:

Testing for differences in average monthly managerial performance before and after replacement of overperforming manager

	Excess Return	Security Selection	Market Timing
t-statistic	-1.42	-0.69	-1.02

** Significant at a 1 % level

* Significant at a 5 % level

We see that the changes are not significant for any of the components. Recall that Khorana (2001) finds that the sample of overperforming funds in the pre-replacement period experience a significant deterioration in subsequent fund return. Based on this, it would be interesting to investigate whether we get a similar result if split the 7 overperformers into a group of 2 with *low overperformers* and *high overperformers*.⁴¹

Table 19 shows the descriptive statistics of the low overperformers, pre- and post-replacement.

TABLE 19:

Arithmetic average monthly excess return, security selection and market timing, and the associated standard deviation and t-statistic for low overperformers pre-replacement

	Excess Return	Security Selection	Market Timing
Average (monthly)	0.170 %	0.447 %	-0.280 %
Stdev (monthly)	0.182 %	0.308 %	0.428 %
t-statistic	1.86	2.91	-1.31

** Significant at a 1 % level

* Significant at a 5 % level

Arithmetic average monthly excess return, security selection and market timing, and the associated standard deviation and t-statistic for low overperformers post-replacement

	Excess Return	Security Selection	Market Timing
Average (monthly)	0.390 %	0.583 %	-0.208 %
Stdev (monthly)	0.236 %	0.183 %	0.368 %
t-statistic	3.30 *	6.38 **	-1.13

** Significant at a 1 % level

* Significant at a 5 % level

⁴¹ We look at the 4 best achievers and the 4 worst achievers (hence, one of the mutual funds ends up in both categories)

Table 20 shows whether the changes are significant:

TABLE 20:

Testing for differences in average monthly managerial performance before and after replacement of low overperforming manager

	Excess Return	Security Selection	Market Timing
t-statistic	1.96	1.01	0.34

** Significant at a 1 % level

* Significant at a 5 % level

The descriptive statistics suggest that the low overperformers pre-replacement are characterized by insignificant managerial performance. When these managers are replaced, we see no significant changes. One reason for this might be that low overperformers have a managerial performance which is quite close to the average performance of all mutual funds (cf. Table 11, pg. 74). This suggests that when these managers are replaced by a new average manager, we should not be able to see any significant changes.

Let us look at the high overperformers. Table 21 shows the descriptive statistics of these funds pre- and post-replacement.

TABLE 21:

Arithmetic average monthly excess return, security selection and market timing, and the associated standard deviation and t-statistic for high overperformers pre-replacement

	Excess Return	Security Selection	Market Timing
Average (monthly)	0.870 %	0.545 %	0.329 %
Stdev (monthly)	0.333 %	0.267 %	0.255 %
t-statistic	5.23 *	4.08 *	2.58

** Significant at a 1 % level

* Significant at a 5 % level

Arithmetic average monthly excess return, security selection and market timing, and the associated standard deviation and t-statistic for high overperformers post-replacement

	Excess Return	Security Selection	Market Timing
Average (monthly)	0.147 %	0.238 %	-0.091 %
Stdev (monthly)	0.457 %	0.292 %	0.208 %
t-statistic	0.65	1.63	-0.88

** Significant at a 1 % level

* Significant at a 5 % level

Table 22 shows whether the changes are significant:

TABLE 22:

Testing for differences in average monthly managerial performance before and after replacement of high overperforming manager

	Excess Return	Security Selection	Market Timing
t-statistic	-3.38 *	-2.05	-3.38 *

** Significant at a 1 % level

* Significant at a 5 % level

The descriptive statistics of the managers pre-replacement suggest that the overperformers are characterized by skills in security selection. When they are replaced, the excess return drops significantly at 5% level. This makes sense, as the very best managers are a scarce resource. If they are offered better positions elsewhere, one would expect it to be hard to find a replacement that is equally good. If the fund's board and investment advisors are only able to attract an average managerial talent, one would expect a decrease in the fund's performance towards the average performance of all funds. Hence, the results underline the importance of trying to keep such managers in the fund. These results are in line with Khorana (2001).

The analysis shows that most of the decline in excess return comes from a decrease in the results in market timing. This could indicate that the very best performers are good in timing the market. However, Table 21 disproves this, since market timing pre-replacement is not significantly different from 0%. Therefore the significant change in market timing is more likely to come from the low sample size.

2.4. Weaknesses of Study

2.4.1. Sample Size

Problem statement 1, 2 and 3 are based on a sample-size of 46, 22 and 14 mutual funds respectively. In problem statement 3, we have decomposed the 14 mutual funds into 2 groups with 7 under and overperformers. Moreover, we have split the overperformers into 2 more groups. Although much of our results are highly significant, it is evident that our sample size should have been larger. However, RBSA requires at least 10 years with return-data to estimate the policy weights. This makes it hard to get large datasets with Norwegian mutual funds. For future research, it would have been interesting to use the two-step RBSA on U.S. data to answer our problem statements.

2.4.2. Survivorship Bias

Survivorship bias occurs when the returns on defunct mutual funds are removed from the sample. Although this is likely to have affected all problem statements, the effect is most evident in problem statement 2 and 3.

In problem statement 2, we use mutual funds that exist as of December 2010, and have close to at least 10 years with return-series. Since defunct funds typically have had poor returns, it is natural that their removals produce an unrealistically high estimate on the existing aggregate mutual fund performance. This is well documented with U.S. data. See e.g. Brown, Goetzmann and Ibbotson (1992) and Malkiel (1995). Using Norwegian data, Sørensen (2009) shows that the difference between the abnormal return of mutual funds that survive and those that die is highly significant. Hence, survivorship bias is likely to overstate the performance of our mutual funds.

In problem statement 3, we investigate what happens to managerial performance after a change in mutual fund management. In some cases, the best alternative is not to change manager, but to close the fund. This is unfortunately not reflected in our analysis, and should be considered in future research.

2.5. Conclusion

In this chapter we have studied three important questions related to Norwegian mutual fund managers: 1) How much of the total variation in mutual fund return is explained by asset allocation, security selection and market timing respectively? 2) Is the average managerial performance positive? 3) Ceteris paribus, does a change in a mutual fund's management cause a change in managerial performance? Let us summarize our findings separately:

2.5.1. Problem statement 1:

The total amount of variation in mutual fund return that is explained by security selection is on average 4.9%, whereas market timing explains 4.5% on average. On average, asset allocation explains 90.6% of the fund's variation in return over time. These results imply that the investor has the largest responsibility for the fund's variability and return over time, since they choose to bet on the risk that follows with the fund's asset allocation. The average Norwegian mutual fund investor should therefore use more time on reviewing their fund's asset allocation and less time on manager searches.

2.5.2. Problem statement 2:

We find that the average excess return is insignificant, even when we include the cost of benchmarking. However, we note that the mutual funds have historically been good in picking stocks. This implies that the Norwegian equity market cannot be efficient in the semi-strong form. Furthermore, we find that the mutual funds could have increased excess return substantially by ceasing to time the market. This suggests that there are reasons to believe that market timing should in general not be undertaken. It is important to stress that the results are prone to survivorship bias.

2.5.3. Problem statement 3:

We find that replacement of poorly performing managers tends to be a value-enhancing activity for both the investment advisors and shareholders of the mutual fund. This implies that market for corporate control in the Norwegian mutual fund industry is effective in disciplining poorly performing fund managers.

By splitting excess return into security selection and market timing, we find that underperforming managers loose because they try to time the market. Moreover, the underperformers seem like they do not possess skills in security selection. Assuming that underperformers are replaced by average performers, we find that average managers avoid market timing, and do not have stock-picking skills.

By analyzing the overperformers, we see that they avoid timing the market. Moreover, they differentiate themselves from the underperformers by being good in stock picking. When we analyze the replacement of the very best managers, we see that excess return declines significantly. This indicates the scarcity of the very best managers, and underlines the importance of trying to keep such managers in the fund.

2.5.4. Implication of Results – and Lessons to be drawn

The empirical evidence generally point in the direction that an investor should spend more time on asset allocation, and less on security selection and market timing. By analyzing mutual fund managers, the results indicate that they should spend more time on security selection, since the Norwegian equity market is inefficient in the semi-strong form. Moreover, the managers should use less time on market timing; by ceasing to time the market, the average manager can substantially increase excess return. In fact, if poor managers cease to utilize market timing, they are likely to avoid getting fired. The best managers already understand this, and enjoy a good reputation and high excess returns.

Let us end the thesis where it started. In Odyssey, we saw that deviations from the predefined route could cause death and injury. Similarly, the temptation of deviating from the predefined policy weights can cause dismantled mutual funds and fired managers. The lesson to be drawn is therefore as follows: to survive in the financial industry, bind yourself to the mast by sticking to your predefined policy weights!

APPENDIX

3.1. APPENDIX A: Definitions

Active Mutual Fund: a mutual fund that attempts to generate return in excess of a given benchmark

Active Return: the mutual fund's actual return in a given asset class

Actual Style-Weights: the mutual fund's exposures to particular asset classes of investments that reflect the fund's movements in the short term

Actual Weight: the mutual fund's proportions placed in particular classes of investments in the beginning of the current period

Asset Allocation: the long-term decision regarding the proportions of total assets that an investor chooses to place in particular classes of investments

Asset Classes: certain categories of investment products

Asset Class Portfolio Series: $\sum_{i=1}^n \beta_{mi} \widetilde{R}_{pit}$

Benchmark (BHB's definition): a passive portfolio with equivalent risk as the mutual fund's asset allocation

Current Allocation: the short-term decision regarding the proportions of total assets that an investor chooses to place in particular that an investor chooses to place in particular classes of investments at the beginning of the current period

Excess Return: the sum of market timing and security selection

Investment Philosophy: a coherent way of thinking about financial markets and how they work

Market Timing: the strategic under- or overweighting of an asset class relative to its policy weight

Passive Mutual Fund: a mutual fund that tries to track a given benchmark

Passive Return: the benchmark return for a given asset class

Policy Style-Weight: the mutual fund's exposures to particular asset classes of investments that reflect the fund's movements in the long run

Policy Weight: the mutual fund's long-term proportion placed in particular classes of investments

Rolling Style Decomposition: the dynamic method of estimating the actual and policy weights for each month in the period under study

Security Selection: the active selection of investments within an asset class.

Style: categorization of assets into broad classes

Style Investing: process of using styles when making portfolio decisions

Style-Weights: weight in a given asset class that reflect the movements of the mutual fund in period $t = T-v$ to $T-1$

v = time length for return-data in RBSA

3.2. APPENDIX B: Testing for Unit-Root

In this appendix we will test the return-series for unit-root using an (Augmented) Dickey Fuller Test. We will first give a short description of the tests, before we show the results:

Dickey-Fuller:

Assume the data generating process for asset class i is as follows:

$$\widetilde{R}p_{i,t} = \alpha + \rho\widetilde{R}p_{i,t-1} + \tilde{\varepsilon}_t$$

where:

$$\begin{aligned}\widetilde{R}p_{i,t} &= \text{Asset class } i \text{'s passive return in period } t \\ \alpha &= \text{Constant} \\ \tilde{\varepsilon}_t &= \text{Noise process}\end{aligned}$$

This seems like a good way of describing our data, since financial return-series do not trend, and are likely to be positive on average. By subtracting $\widetilde{R}p_{i,t-1}$ on the left and right hand side, we get the following expression:

$$\begin{aligned}\widetilde{R}p_{i,t} - \widetilde{R}p_{i,t-1} &= \alpha + (\rho - 1)\widetilde{R}p_{i,t-1} + \tilde{\varepsilon}_t \rightarrow \\ \Delta\widetilde{R}p_{i,t} &= \alpha + \theta\widetilde{R}p_{i,t-1} + \tilde{\varepsilon}_t, \text{ where } \theta = \rho - 1\end{aligned}$$

We can then test for stationarity using the following hypothesis:

$$\begin{aligned}H_0: \theta = 0 &\leftrightarrow \rho = 1 \rightarrow \text{Unit Root} \\ H_1: \theta < 0 &\leftrightarrow \rho > 1 \rightarrow \text{Stationary Process}\end{aligned}$$

Augmented Dickey-Fuller:

We can also control for the possibility that $\tilde{\varepsilon}_t$ can be correlated with lags of $\widetilde{R}p_{i,t}$ through the use of an Augmented Dickey Fuller test:

$$\Delta\widetilde{R}p_{i,t} = \alpha + \theta\widetilde{R}p_{i,t-1} + \sum_{i=1}^P \gamma_i \Delta\widetilde{R}p_{i,t-i} + \tilde{\varepsilon}_t$$

Our hypothesis is as follows:

$$H_0: \theta = 0 \leftrightarrow \rho = 1 \rightarrow \text{Unit Root}$$

$$H_1: \theta < 0 \leftrightarrow \rho > 1 \rightarrow \text{Stationary Process}$$

Results:

When testing for unit-root in the 10 asset classes, we get the following results:

(Augmented) Dickey Fuller Test for return-series.
 Period: Jan. 1995 – Dec. 2010

Variable	θ	t-value		Lags	Trend?	Constant?
S	-0.76	-10.529	**	0	No	Yes
MG	-0.89	-12.16	**	0	No	Yes
MV	-0.92	-12.491	**	0	No	Yes
LG	-0.99	-13.346	**	0	No	Yes
LV	-1.02	-13.783	**	0	No	Yes
W	-0.88	-12.025	**	0	No	Yes
E	-0.83	-11.476	**	0	No	Yes
3M	-0.02	-1.2996		1	No	Yes
3Y	-0.02	-1.5748		1	No	Yes
10Y	-0.03	-2.1021		1	No	Yes

* Significant at 5 % level. Critical value = -2.877

** Significant at 1 % level. Critical value = -3.467

Conclusion: we cannot reject H_0 for bonds and bills. We tested the bills and bonds with other lag-lengths as well, but the conclusion did not change

3.3. APPENDIX C: Confidence Interval of Style-Weights

This proof is based on Lobosco and DiBartolomeo (1997). Consider the case where we actually have the true style-weights, β_{mi} . The tracking error is then as follows:

$$\tilde{e}_{mt} = \tilde{r}_{mt} - \sum_{i=1}^n \beta_{mi} \widetilde{R}p_{it}; \quad t = T-v, T-v+1, \dots, T-1$$

Consider the extent to which the estimates for the style-weights do not march the true style-weights:

$$\hat{\beta}_{mi} = \beta_{mi} + \Delta\beta_{mi}$$

where:

$$\begin{aligned} \hat{\beta}_{mi} &= \text{Mutual fund } m\text{'s estimated style-weight for asset class } i \\ \beta_{mi} &= \text{Mutual fund } m\text{'s (true) style-weight for asset class } i \\ \Delta\beta_{mi} &= \text{Amount of error in the estimate of mutual fund } m\text{'s style-weight for} \\ &\quad \text{asset class } i \end{aligned}$$

Style analysis can only reliably attribute portfolio returns to the portions of asset class returns that are themselves not attributable to the returns of the other asset classes. In order to get an estimate of the amount of error in the style-weights, the fitting process must therefore somehow isolate the portion of the asset classes' returns that are independent of the other asset classes used in the analysis. To isolate this independent portion of each index, one can define:

$$\tilde{T}_{it} = \sum v_j \widetilde{R}p_{jt} \text{ (for } j \neq i \text{)}; \quad t = T-v, T-v+1, \dots, T-1$$

and

$$\sum v_j = 1 \text{ (for } m \neq i \text{)}$$

where:

$$\begin{aligned} \tilde{T}_i &= \text{Asset class } i\text{'s return-series analyzed against all asset classes exclusive} \\ &\quad \text{of } i \\ v_j &= \text{Style-weight on asset class } j \\ \widetilde{R}p_{jt} &= \text{Passive returns of asset class } j \end{aligned}$$

Note that we do not have any constraints on these weights saying that they should be in the range 0 to 1. We now define:

$$\tilde{B}_{it} = \tilde{R}p_{it} - \tilde{T}_{it}; \quad t = T-v, T-v+1, \dots, T-1$$

where:

$$\tilde{B}_{it} = \text{Portion of the returns on asset class } i \text{ not attributable to the other asset classes, subject to the constraint } \sum v_j = 1 \text{ (for } j \neq i\text{)}.$$

We have now got expressions for both the error in the style-weights ($\Delta\beta_{mi}$) and the independent portions of the asset class behaviors (\tilde{B}_{it}). Only through the interaction of these two sets of values can the goodness of fit be varied. It can be shown that the operative process in style analysis is to try to minimize the variance of $\tilde{r}_{mt} - \sum_{i=1}^n \beta_{mi} \tilde{R}p_{it} - (\Delta\beta_{mi} \tilde{B}_{it})$ for each t , or equivalently, minimize the variance of $\tilde{e}_{mt} - (\Delta\beta_{mi} \tilde{B}_{it})$ for each t . One can set an objective function, Z , to this expression:

$$Z = \text{Var}(\tilde{e}_{mt} - \Delta\beta_{mi} \tilde{B}_{it}) = \sigma_e^2 + \Delta\beta_{mi}^2 \sigma_B^2 - 2\Delta\beta_{mi} \sigma_e \sigma_B \rho_{e,B}$$

where:

$$\begin{aligned} \sigma &= \text{Sample standard deviation} \\ \rho &= \text{Sample correlation coefficient} \\ e &= \text{Simplification of } \tilde{e}_{mt} \\ B &= \text{Simplification of } \tilde{B}_{it} \end{aligned}$$

To solve for the minimum of the variance, we set the derivative of the variance with respect to the style-weights equal to zero:

$$\begin{aligned} \frac{dZ}{d\Delta\beta_{mi}} &= 2\Delta\beta_{mi} \sigma_B^2 - 2\sigma_e \sigma_B \rho_{e,B} \\ \frac{dZ}{d\Delta\beta_{mi}} &= 0 \text{ if and only if } \Delta\beta_{mi} = \frac{\sigma_e \rho_{e,B}}{\sigma_B} \end{aligned}$$

Because the standard deviation for ρ is approximately $\frac{1}{\sqrt{v-2}}$, the standard deviation of $\Delta\beta_{mi}$ is approximated by

$$\sigma_{\Delta\beta_{mi}} \cong \frac{\sigma_e}{\sigma_B \sqrt{v-2}}$$

where:

$$v = \text{Time length of return-series}$$

Because we do not know the true style-weights, we do not know σ_e . However, we know the standard error of the estimated tracking error:

$$\hat{\tilde{e}}_{mt} = \tilde{r}_{mt} - \sum_{i=1}^n (\beta_{mi} + \Delta\beta_{mi}) \cdot \tilde{R}p_{it}; \quad t = T-v, T-v+1, \dots, T-1$$

We abbreviate $\hat{\tilde{e}}_{mt}$ with \hat{e} . Because \hat{e} has $(v-k)$ degree of freedom and e (\tilde{e}_{mt}) has $(v-1)$ degrees of freedom, one can use the relation:

$$\sigma_{\hat{e}}^2 = \frac{\sigma_e^2 (v-k)}{(v-1)}$$

where:

$$k = \text{Number of asset classes with nonzero style-weights}$$

This can be rearranged and put back into the equation for $\sigma_{\Delta\beta_{mi}}$ to get

$$\sigma_{\Delta\beta_{mi}} = \frac{\sigma_{\hat{e}}}{\sigma_B \cdot \sqrt{v-k-1}}$$

3.4. APPENDIX D: Current Mutual Funds

List of Current active Norwegian mutual funds, with focus on Norwegian equity and have long-positions only:

Mutual Funds	Start date	Mutual Funds	Start date
Alfred Berg Aktiv	29.12.1995	Fondsfinans Aktiv	04.04.2000
Alfred Berg Aktiv II	15.09.1997	Handelsbanken Norge Acc	06.03.1995
Alfred Berg Gambak	01.11.1990	Holberg Norge	28.12.2000
Alfred Berg Humanfond	15.12.1999	KLP AksjeNorge	12.03.1999
Alfred Berg Norge + Acc	04.12.1997	NB Aksjefond	01.08.1996
Alfred Berg Norge Acc	01.10.1990	Nordea Avkastning	01.02.1981
Atlas Norge	24.02.1998	Nordea Kapital	01.01.1995
Avanse Norge (I)	01.10.1966	Nordea Norge Verdi	02.02.1996
Avanse Norge (II)	07.12.1990	Nordea SMB	21.05.1997
Carnegie Aksje Norge Acc	07.07.1995	Nordea Vekst	01.02.1981
Danske Invest Norge I	03.01.1994	ODIN Norge Acc	26.06.1992
Danske Invest Norge II	03.01.1994	Orkla Finans Investment	03.01.1985
Danske Invest Norge Vekst	03.01.1994	PLUS Aksje (Fondsforvaltning)	27.12.1996
Danske Invest Norske Aksjer Inst I Acc	13.04.2000	PLUS Markedsverdi (Fondsforvaltning)	31.05.1994
Delphi Norge	03.06.1994	Postbanken Norge	27.07.1995
Delphi Vekst	20.10.1997	Storebrand Aksje Innland	01.07.1996
DnB NOR Barnefond	17.02.1997	Storebrand Norge	14.09.1983
DnB NOR Norge (I)	24.10.1981	Storebrand Norge I	03.04.2000
DnB NOR Norge (III)	06.02.1996	Storebrand Optima Norge A	28.12.2000
DnB NOR Norge Selektiv (I)	19.04.1996	Storebrand Vekst	09.10.1992
DnB NOR Norge Selektiv (II)	19.12.2001	Storebrand Verdi	22.12.1997
DnB NOR Norge Selektiv (III)	13.06.1994	Terra Norge	03.04.1998
DnB NOR SMB	16.03.2001	Terra SMB	01.04.1998
Total number of mutal funds:	46		

Source: Morningstar

3.5. APPENDIX E:

(Augmented) Dickey Fuller Test for return-series

Period: Jan. 2001-Dec. 2010***

Mutual Fund	θ	t-value	Lags	Trend?	Constant?
Alfred Berg Aktiv	-0,64	-5,05 **	1	No	Yes
Alfred Berg Aktiv II	-0,80	-6,05 **	1	No	Yes
Alfred Berg Gambak	-0,68	-5,18 **	1	No	Yes
Alfred Berg Humanfond	-0,94	-6,80 **	1	No	Yes
Alfred Berg Norge + Acc	-0,94	-6,79 **	1	No	Yes
Alfred Berg Norge Acc	-0,83	-6,10 **	1	No	Yes
Atlas Norge	-0,88	-6,64 **	1	No	Yes
Avanse Norge (I)	-0,96	-6,52 **	1	No	Yes
Avanse Norge (II)	-0,87	-6,30 **	1	No	Yes
Carnegie Aksje Norge Acc	-0,88	-6,50 **	1	No	Yes
Danske Invest Norge I	-1,04	-7,34 **	1	No	Yes
Danske Invest Norge II	-1,04	-7,37 **	1	No	Yes
Danske Invest Norge Vekst	-0,62	-5,05 **	1	No	Yes
Danske Invest Norske Aksjer Inst I Acc	-0,86	-6,09 **	1	No	Yes
Delphi Norge	-0,88	-6,36 **	1	No	Yes
Delphi Vekst	-0,89	-6,61 **	1	No	Yes
DnB NOR Barnefond	-0,91	-6,55 **	1	No	Yes
DnB NOR Norge (I)	-1,05	-11,55 **	1	No	Yes
DnB NOR Norge (III)	-0,87	-6,33 **	1	No	Yes
DnB NOR Norge Selektiv (I)	-0,89	-6,57 **	1	No	Yes
DnB NOR Norge Selektiv (II)	-0,71	-5,40 **	1	No	Yes
DnB NOR Norge Selektiv (III)	-0,82	-6,07 **	1	No	Yes
DnB NOR SMB	-0,63	-5,12 **	1	No	Yes
Fondsfinans Aktiv	-0,86	-6,04 **	1	No	Yes
Handelsbanken Norge Acc	-0,82	-6,19 **	1	No	Yes
Holberg Norge	-0,69	-5,48 **	1	No	Yes
KLP AksjeNorge	-0,91	-6,59 **	1	No	Yes
NB Aksjefond	-0,95	-6,97 **	1	No	Yes
Nordea Avkastning	-1,05	-6,84 **	1	No	Yes
Nordea Kapital	-0,85	-6,28 **	1	No	Yes
Nordea Norge Verdi	-0,76	-5,72 **	1	No	Yes
Nordea SMB	-0,73	-5,73 **	1	No	Yes
Nordea Vekst	-0,89	-8,43 **	1	No	Yes
ODIN Norge Acc	-0,68	-5,56 **	1	No	Yes
Orkla Finans Investment	-0,82	-6,01 **	1	No	Yes
PLUSS Aksje (Fondsforvaltning)	-1,00	-7,03 **	1	No	Yes
PLUSS Markedsverdi (Fondsforvaltning)	-1,06	-7,49 **	1	No	Yes
Postbanken Norge	-0,90	-6,72 **	1	No	Yes
Storebrand Aksje Innland	-0,89	-6,44 **	1	No	Yes
Storebrand Norge	-0,96	-6,82 **	1	No	Yes
Storebrand Norge I	-0,90	-6,25 **	1	No	Yes
Storebrand Optima Norge A	-0,73	-5,51 **	1	No	Yes
Storebrand Vekst	-0,74	-5,60 **	1	No	Yes
Storebrand Verdi	-0,97	-6,89 **	1	No	Yes
Terra Norge	-0,90	-6,63 **	1	No	Yes
Terra SMB	-0,98	-7,07 **	1	No	Yes

** Significant at 1 % level. Critical value = -3.501

* Significant at 5 % level. Critical value = -2.892

*** Some of these series have close to 10 years with return data, but do not start in Jan. 2001

3.6. APPENDIX F: Mutual funds in Problem Statement 2

List of Mutual Funds used in problem statement 2:

Mutual Fund with start date before 1996	Start date
Alfred Berg Aktiv	12/29/1995
Alfred Berg Gambak	11/1/1990
Alfred Berg Norge Acc	10/1/1990
Avanse Norge (I)	10/1/1966
Avanse Norge (II)	12/7/1990
Carnegie Aksje Norge Acc	7/7/1995
Danske Invest Norge I	1/3/1994
Danske Invest Norge II	1/3/1994
Danske Invest Norge Vekst	1/3/1994
Delphi Norge	6/3/1994
DnB NOR Norge (I)	10/24/1981
DnB NOR Norge Selektiv (III)	6/13/1994
Handelsbanken Norge Acc	3/6/1995
Nordea Avkastning	2/1/1981
Nordea Kapital	1/1/1995
Nordea Vekst	2/1/1981
ODIN Norge Acc	6/26/1992
Orkla Finans Investment	1/3/1985
PLUSS Markedsverdi (Fondsforvaltning)	5/31/1994
Postbanken Norge	7/27/1995
Storebrand Norge	9/14/1983
Storebrand Vekst	10/9/1992
Total number of mutal funds:	22

Source: Morningstar

3.7. APPENDIX G: Mutual funds in Problem Statement 3

Mutual Funds used in problem statement 3:

Mutual Fund	Start Date	Last Change in Manager	Over or Under- performer before change? (O/U?)
Avanse Norge (I)	10/1/1966	8/1/2007	U
Avanse Norge (II)	12/7/1990	8/1/2007	O
Danske Invest Norge I	1/3/1994	11/29/2006	U
Danske Invest Norge II	1/3/1994	11/29/2006	U
Danske Invest Norge Vekst	1/3/1994	4/1/2006	U
Delphi Norge	6/3/1994	12/1/2007	O
DnB NOR Norge (I)	10/24/1981	4/13/2005	O
DnB NOR Norge Selektiv (I)	4/19/1996	8/1/2007	U
DnB NOR Norge Selektiv (III)	6/13/1994	8/1/2007	O
NB Aksjefond	8/1/1996	9/1/2007	U
Nordea Avkastning	2/1/1981	4/29/2004	O
Orkla Finans Investment	1/3/1985	1/1/2007	U
Postbanken Norge	7/27/1995	7/4/2006	O
Storebrand Norge	9/14/1983	1/1/2007	O
Total number of mutual funds:	14		

Source: Morningstar

3.8. APPENDIX H: Average return

Geometric average monthly Excess Return, Security Selection and Market Timing, 2006 – 2010

Mutual Fund	Cost Included			Cost Excluded		
	Excess Return	Security Selection	Market Timing	Excess Return	Security Selection	Market Timing
Alfred Berg Aktiv	0,024 %	0,255 %	-0,231 %	0,004 %	0,235 %	-0,231 %
Alfred Berg Gambak	0,243 %	0,354 %	-0,112 %	0,223 %	0,334 %	-0,112 %
Alfred Berg Norge Acc	0,012 %	0,262 %	-0,250 %	-0,008 %	0,242 %	-0,250 %
Avanse Norge (I)	-0,096 %	0,171 %	-0,266 %	-0,116 %	0,151 %	-0,266 %
Avanse Norge II	-0,032 %	0,204 %	-0,237 %	-0,052 %	0,184 %	-0,237 %
Carnegie Aksje Norge Acc	0,107 %	0,333 %	-0,227 %	0,087 %	0,313 %	-0,227 %
Danske Invest Norge I	0,070 %	0,409 %	-0,340 %	0,050 %	0,389 %	-0,340 %
Danske Invest Norge II	0,144 %	0,493 %	-0,349 %	0,124 %	0,473 %	-0,349 %
Danske Invest Norge Vekst	-0,167 %	-0,286 %	0,119 %	-0,187 %	-0,306 %	0,119 %
Delphi Norge	0,219 %	-0,035 %	0,254 %	0,199 %	-0,055 %	0,254 %
DnB Nor Norge (I)	0,058 %	0,399 %	-0,341 %	0,038 %	0,379 %	-0,341 %
DnB NOR Norge Selektiv (III)	0,185 %	0,407 %	-0,223 %	0,165 %	0,387 %	-0,223 %
Handelsbanken Norge Acc	0,040 %	0,274 %	-0,234 %	0,020 %	0,254 %	-0,234 %
Nordea Avkastning	-0,010 %	0,229 %	-0,239 %	-0,030 %	0,209 %	-0,239 %
Nordea Kapital	0,009 %	0,256 %	-0,247 %	-0,011 %	0,236 %	-0,247 %
Nordea Vekst	-0,220 %	0,150 %	-0,370 %	-0,240 %	0,130 %	-0,370 %
Odin Norge Acc	-0,348 %	-0,524 %	0,176 %	-0,368 %	-0,544 %	0,176 %
Orkla Finans Investment Fund	-0,377 %	-0,213 %	-0,165 %	-0,397 %	-0,233 %	-0,165 %
PLUSS Markedsverdi (Fondsforvaltning)	0,071 %	0,346 %	-0,275 %	0,051 %	0,326 %	-0,275 %
Postbanken Norge	0,061 %	0,403 %	-0,342 %	0,041 %	0,383 %	-0,342 %
Storebrand Norge	0,043 %	0,227 %	-0,184 %	0,023 %	0,207 %	-0,184 %
Storebrand Vekst	0,297 %	0,182 %	0,116 %	0,277 %	0,162 %	0,116 %

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