Empirical analysis of investment strategies for institutional investors

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ter verkrijging van de graad van doctor aan de Universiteit van Tilburg, op gezag van de rector magnificus, prof. dr. F.A. van der Duyn Schouten, in het openbaar te verdedigen ten overstaan van een door het college voor promoties aangewezen commissie in de aula van de Universiteit op woensdag 17 december 2003 om 16.15 uur door

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Preface

Parts of this study are written in cooperation with others and are based on other publications. From Part I is based on Swinkels (2003), Swinkels (2002), and Nijman, Swinkels & Verbeek (2003). Part II is derived from Nijman & Swinkels (2003a) and Nijman & Swinkels (2003b). Part III of this thesis has appeard before as Swinkels & Van Der Sluis (2001) and Swinkels, Van der Sluis & Verbeek (2003).

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My office at the Econometrics Department and my affiliation with the CentER research group Finance has given me the opportunity to keep fit by taking the stairs to/from their respective floors. I would like to thank the colleagues from both the Econometrics and Finance Departments and my fellow PhD students for the pleasant working environment. I especially want to mention Jeroen Kerkhof, with whom I shared the most luxurious PhD office for more than three years. Special thanks also goes to the secretaries who have been always there to assist me.

Last but not least I want to express gratitude towards my family and friends. Their support has been invaluable. Involving me in activities such as sports, concerts, and an occasional beer has given me the necessary strength to keep working on this thesis.

Ieva, knowing you has given me inspiration to develop myself in many directions, pursuing a PhD being only one of them.

Contents

Chapter 1

Introduction

This thesis consists of three parts. The first part, entitled *"Momentum strategies"*, deals with the empirical observation that stocks with a relatively high return over the past half year realize higher returns than stocks with a relatively low return in the next three to twelve months. This momentum phenomenon has been subject of a lively debate, but conclusive evidence about its explanation has not been provided yet. We further examine the influence of countries and industries on the momentum effect in the European stock market. In the second part, entitled *"Asset allocation for pension funds"*, the influence of regulatory developments on the optimal asset allocation, including alternative asset categories such as commodities and hedge funds, is analyzed in further detail. The third and last part, entitled *"Mutual fund style and performance measurement"*, introduces a novel technique to improve the estimation of the investment style of mutual funds, and analyze the impact of the ability of fund managers to beat the market by switching between cash and stocks on basis of the conditional expected return of these funds. In this introductory chapter, we motivate the questions analyzed in this thesis and describe the main contributions of each of the chapters.

1.1 Motivation

Institutional investing has become increasingly important in everyday life. Most employers and employees agree on a pension scheme, in which current salary payments are postponed for later. Pension funds are institutions that are designed to look after the salary contributions and pay out retirement benefits when fund members reach the retirement age. The recent solvency problems of part of these funds have increased the demand for improved regulation on the behavior of their managers. The assets under management of pension funds are enormous. In the US, the combined asset value of private and public pension funds reached \$ 10.9 trillion (€ 10 trillion) at the end of 2001.[1] In the UK, pension funds assets totaled £ 0.78 trillion (€ 1.2 trillion) ultimo June 2002.[2] The roughly 1,000 pension funds in The Netherlands managed about € 472 billion at the end of 2001.[3] This means that the pension savings per capita are € 29,000, € 20,000, and € 30,000 in the US, UK, and The Netherlands, respectively. These numbers indicate the importance of the analysis of the investment behavior and performance of these financial institutions. In this thesis, we analyze the optimal asset allocation of pension funds, taking into account regulatory developments, and investigating alternative strategies that might reduce solvency risk of pension funds.

In addition to savings designated for retirement, people may save privately. These savings can be stored on a bank account, but also be managed professionally by mutual funds. In the US over 8,000 mutual funds are listed, with in total \$ 7.0 trillion assets under management (about \$ 2.4 trillion of these are designated retirement savings) at the end of 2001. The size of the European mutual fund market was € 3.6 trillion ultimo 2001, with The Netherlands accounting for € 89 billion spread out over roughly 400 funds. Whereas employees, especially in Europe, have limited or no choice in which pension fund they want to participate, investments in mutual funds are almost unconstrained. Thus, instead of constructing an optimal portfolio of stocks or bonds, the investment opportunity set for an individual investor has increased by a large number of investment funds, divided into categories on the basis of their investment style. The advantages of mutual funds are that transactions costs are generally low, a well-diversified portfolio can be obtained with a limited investment, and they provide additional customer services such as annual tax balance sheet reports or investment advice. Given the unusually high stock returns in the latter half of the 1990s, and the disappointing stock returns since early 2000, a manager with the ability to time the market could have substantially outperformed a passive portfolio. In this thesis, we both investigate how to estimate the investment style of mutual funds, as well as the influence of the ability of fund managers to time between stocks and cash on the conditional expected fund return.

1.2 Contribution of the thesis

Part I of the thesis deals with stock return continuation, or momentum, and consists of three chapters. Chapter 2 is a survey on the existing literature on momentum strategies. Since the seminal paper on momentum strategies by Jegadeesh & Titman (1993), research papers about the existence of stock return continuation have been abundant. Chapter 2

[1] Sources: Investment Company Institute (June 2002), Employee Benefit Research Institute (May 2002).
[2] Source: Investment Management Association (2003).
[3] Source: Pensioen- en Verzekeringskamer (2002).

starts with empirical evidence on the momentum effect, followed by an empirical decomposition of factors that might drive the momentum effect. The empirical relation between momentum and other firm characteristics is also described. We furthermore present various behavioral and risk-based explanations of the momentum effect. Recent estimates of transactions costs incurred while executing a momentum strategy suggest that up to a certain portfolio size the momentum effect can be exploited. Until a firm establishment of all stylized facts that have been claimed in the literature and plausible explanations for the momentum effect are found, this area is expected to remain a fruitful area of future research.

In Chapter 3 we analyze the existence of industry momentum, which Moskowitz & Grinblatt (1999) claim to be the driving force behind momentum strategies on individual stocks. We confirm the existence of industry momentum for the US stock market using a different industry classification scheme than Moskowitz & Grinblatt. We find that the industry momentum effect is also present in the European stock market. For the Japanese stock market, we find little support for the industry momentum effect, which is not surprising since other studies claim that there is no return continuation when Japanese stocks are investigated individually. In addition, we examine the lead-lag relation between these three regions. We rank industries on their past returns in one region, and subsequently invest in the same industries in the other regions. We find that a strategy that ranks on US industries and subsequently invests in European industries is stronger on a longer investment horizon than traditional strategies using past returns of industries within the same region. Similarly, ranking on European and investing in Japanese industries also increases expected returns on a one-year horizon. Using this cross-border information may enhance trading strategies trying to exploit the industry momentum effect in Europe and Japan.

Chapter 4 contributes to the momentum debate by investigating the presence of country and industry momentum in Europe and addressing the question whether individual stock momentum is subsumed by country or industry momentum. We examine these issues by introducing a portfolio-based regression approach, which allows testing hypotheses about the existence and relative importance of multiple effects using standard statistical techniques. Traditional sorting techniques are not suited to disentangle a multitude of possibly interrelated effects (e.g. momentum, value, and size). Our method can be used even when only a moderate number of stocks are available. Our results suggest that individual stocks effects primarily drive the positive expected excess returns of momentum strategies in European stock markets, while industry momentum plays a less important role and country momentum is even weaker. These results are robust to the inclusion of value and size effects.

Part II of the thesis analyzes two topics with respect to the optimal asset allocation of pension funds. Chapter 5 examines the incentive changes caused by new developments in pension fund regulations and their implementation in The Netherlands. An imminent change at the national level is the shift from actuarial to market-based valuation of the liabilities in the pension fund portfolio. The traditional maximum discount rate of four percent will lose importance in the new Financial Assessment Framework (FTK), exposing bonds on the asset side as a natural hedge for the pension claims on the liability side. The Dutch regulatory authority that supervises insurance companies and pension funds (PVK) clarified its interpretation of the rules by sending a letter to all pension fund boards in Septermber 2002. The maximum expected return on stocks in asset liability management (ALM) studies is restricted to be considerably below the historical average that is often used as an estimator for future returns, making bonds relatively more attractive than before. International changes influencing pension fund asset allocation are also imminent. The international accounting standards (IAS) require that pension surpluses or deficits are immediately activated on the balance sheet of the parent company. In order to reduce the volatility of company operating profits, pension funds might be requested by the firm to reduce the uncertainty in the funding ratio by investing more in bonds. European regulation of the pension fund industry is still limited, but we expect that further developments in the regulation and supervision at the European level also affect optimal pension fund allocations in the future.

In Chapter 6, we examine whether extending the set of traditional investment opportunities with commodities can reduce the variance risk of investment portfolios of pension schemes investing in traditional asset classes. We investigate the economic and statistical significance of shifts in the strategic (three year), myopic (quarterly), and tactical (quarterly rebalancing) mean-variance frontier for pension schemes with a fixed liability portfolio. We find substantial differences in optimal strategic allocations for pension schemes with nominal and inflation-indexed pensions. While our results suggest that commodities reduce the risk on the funding ratio from an inflation-indexed scheme by more than 30 percent, the optimal expected return and risk trade-off is unaffected for pension schemes with nominal claims. Similar results are obtained for the unconditional myopic investor with a quarterly investment horizon. When conditioning information about the macro economic situation is used, a pension scheme with nominal claims can during certain periods also improve its efficient risk-return trade-off by investing in commodities. Moreover, we investigate the use of quarterly timing strategies switching between commodities and stocks, in addition to the buy-and-hold investments in the traditional assets and commodities. Both for nominal and real pension schemes, timing strategies can be useful in addition to the strategic allocation. The liability hedging property of commodities is likely to reduce the probability of underfunding.

In Part III of the thesis, the investment style and performance of mutual funds is analyzed in more detail. Chapter 7 focuses on the estimation of mutual fund styles by return-based style analysis. Often the investment style is assumed to be constant through time. Alternatively, time variation is sometimes implicitly accounted for by using rolling regressions when estimating the style exposures. The former assumption is often contradicted empirically, and the latter is inefficient due to its ad hoc chosen window size. We propose to use the Kalman filter to model time-varying exposures of mutual funds explicitly. This leads to a testable model and more efficient use of the data, which reduces the influence of spurious correlation between mutual fund returns and style indices. Several stylized examples indicate that more reliable style estimates can be obtained by modeling the style exposure as a random walk, and estimating the coefficients with the Kalman filter. The differences with traditional techniques are substantial in our stylized examples. The results from our empirical analysis indicate that the structural model estimated by the Kalman filter improves style predictions and influences results on performance measurement. A recent paper by Spiegel, Mamaysky & Zhang (2003) uses the Kalman filtered alphas and betas to select mutual funds and show that this leads to improved investment decisions relative to selection based on alphas and betas estimated by OLS.

In Chapter 8, we decompose the conditional expected mutual fund return in five parts. Two parts, selectivity and expert market timing, can be attributed to manager skill, and three to variation in beta that can be achieved by private investors as well. The dynamic model that we use to estimate the relative importance of the components in the decomposition is a generalization of the performance evaluation models by Lockwood & Kadiyala (1988) and Ferson & Schadt (1996). The results from our sample of 78 asset allocation mutual funds indicate that several funds exhibit significant expert market timing, but for most funds variation in market exposures does not yield any economically significant return. Our results further suggest that funds with high turnover and expense ratios are associated with managers with better skills.

Finally, Chapter 9 provides a summary of the main conclusions from this thesis.

Part I

Momentum strategies

Chapter 2

Momentum investing: A survey

2.1 Introduction

Simple trading strategies have attracted attention since the early days of stock trading.[1] Probably the most obvious strategies are trading strategies which are based on the past return pattern of stocks. In this chapter, we summarize the existing literature on patterns of return continuation. We focus on cross-sectional patterns, i.e., the relation between the relative return of a stock versus the market based on its relative return in the previous period, instead of the time-series predictability known as technical analysis.[2] These cross-sectional patterns are called momentum or contrarian strategies, depending on return continuation or reversals in the subsequent investment horizon. A momentum (contrarian) strategy is based on a simple rule; buy stocks that performed best (worst) and sell stocks that performed worst (best) in the recent past. We focus on strategies that examine medium term return continuation.

In Section 2.2 we discuss the empirical findings in the momentum literature. The seminal paper on the momentum effect is Jegadeesh & Titman (1993), who suggest that high returns continue to be high and low returns continue to be low on a horizon of 3–12 months. They find an excess return of about 12 percent per year for US stocks on a zero-investment portfolio long in stocks with high, and short in stocks with low six-month returns.[3] Several authors have gathered out-of-sample evidence on the momentum effect for other stock markets. Moreover, Jegadeesh & Titman (2001) claim that momentum is present in an out-of-sample period, the decade after their initial observation. These

[1] See Cootner (1964) for an overview of early academic work on the behavior of stock market prices.

[2] Return patterns discovered by these technical analysts or chartists (with mysterious names like head-and-shoulders or triangle tops) seem to be highly subjective and therefore hard to analyze. Lo, Mamaysky & Wang (2000) attempt to formalize these return patterns and develop algorithms to detect them.

[3] In fact, the long-short strategies presented in Jegadeesh & Titman (1993) are not based on truly zero-investment (or self-financing) portfolios, since they rebalance their portfolios each month.

findings cast doubt on the explanation that extensive data-snooping by researchers has resulted in misleading statistical evidence about the momentum effect.

At the intermediate horizon, returns seem to move the opposite way from the short and long term. The results by DeBondt & Thaler (1985) suggest that stock returns in the US show reversals on the long term. They indicate that a portfolio of stocks with lowest returns over the past 3–5 years outperforms a portfolio of stocks with highest returns in the following 3-5 years with roughly 8 percent per year. Return reversals have also been documented on the very short term; see e.g. Jegadeesh (1990). He claims to find a highly significant negative autocorrelation in monthly stock returns, and indicates that a trading strategy which exploits this one-month reversal has an average excess return of almost 30 percent per year, excluding trading costs.[4]

The debate about momentum strategies has shifted from providing empirical evidence about its existence to empirical analyses of the various components and theory-based explanations. While a descriptive data analysis may provide meaningful insight in the determinants of return continuation, a theoretical explanation may supply additional structure and might set out the (economic) conditions under which we can expect a future momentum effect as well. The momentum effect is defined in the literature as the cross sectional covariance of the successive returns of a sample of stocks. A covariance decomposition can be used in order to gain more insight in the relative importance of the factors in the return decomposition. In Section 2.3, we present the decomposition from Moskowitz & Grinblatt (1999), and reinterpret it in such way that it encompasses most existing empirical research.

In Section 2.4 we consider more recent empirical results on the momentum effect that relate to the decomposition presented in Section 2.3. In addition to the US stock market, we pay attention to international evidence on the momentum phenomenon. We also investigate the relation of momentum strategies with other conditioning variables, such as the market capitalization and trading volume of the stock. This section also includes the influences of the industry and country composition of momentum portfolios.

Section 2.5 presents the current findings on risk-based explanations. While the decomposition from Section 2.3 may provide insights into the driving force behind the momentum effect, it does not explain why the momentum effect exists in the first place. Understanding the source and nature of momentum profits seems indispensable when it comes to statements about the possible persistence of stock return continuation. One line of literature argues that the expected excess return on momentum strategies are a compensation for higher risk. Simple risk measures such as the standard deviation or differences in market exposures do not seem to be able to explain the positive expected return. Fama & French

[4]See Section 2.7 for a more elaborate discussion on the expected transaction costs involving momentum strategies.

(1996) point out that the unconditional three-factor model of Fama & French (1993) also cannot explain momentum returns. This in contrast to the long-term contrarian strategies of DeBondt & Thaler (1985). Carhart (1997) recognizes the importance of the momentum effect and uses a four-factor model to evaluate the investment performance of mutual funds by adding a momentum factor to the asset pricing model with a market, value, and size risk factor. Recently, several papers have appeared that try to link macro economic risks with the profitability of momentum strategies. It appears that conditional factor models might be able to capture the momentum effect.

Another strand of explanations is provided by behavioral finance. More insight into these type of explanations for the momentum effect is presented in Section 2.6. In contrast to risk-based explanations, this research makes use of explicit assumptions on the behavior of investors. This behavior may or may not be irrational, and can be based on known psychological phenomena. Irrational decisions may lead to systematic under- or overreaction of prices relative to their fundamental value, whatever that may be. Examples of this type of models are Daniel, Hirshleifer & Subrahmanyam (1998) and Barberis, Shleifer & Vishny (1998). They use different assumptions about investor behavior which are both able to generate a momentum effect. Other behavioral models rely on rational behavior of investors with heterogeneous characteristics. An example of this research is Hong & Stein (1999), who discriminate two types of investors. The first type watches the firm news, while the other bases his investment decisions only on the most recent return of a stock, because gathering news is considered too expensive.

In Section 2.7 the role of transactions costs on the expected return of the momentum trading strategy is investigated in more detail. The round-trip (one buy, one sell) transactions costs, which typically include bid-ask spread, broker commission, and market impact, are incurred at most twice per year for a strategy with a six month holding period.[5] These costs could potentially offset the 12 percent per annum gain that is reported in Jegadeesh & Titman (1993). While in several studies round-trip transactions costs are documented close to one percent, several authors have noted that momentum stocks might be more expensive to trade. Korajczyk & Sadka (2003) find that momentum profits disappear for portfolios larger than $ 1 billion. Lesmond, Schill & Zhou (2003) claim that momentum stocks are particularly costly to trade. They suggest that momentum profits are illusionary, because market frictions cause these apparently positive expected returns. These frictions may prevent investors to actually implement these effects with positive expected return. Note, however, that even when large investors might not be able to implement momentum strategies on a large scale, this by itself does not explain the

[5]The actual transactions costs are incurred less than twice a year due to stocks that remain in the winner or loser portfolio and need not be traded after the holding period.

existence of return continuation.

Recapitulating, the plan of this survey chapter is as follows. In Section 2.2, we describe the empirical evidence on the momentum effect for the US market, analyzing research methods frequently used in this field. In Section 2.3, a cross-sectional return decomposition is made in order to attribute momentum effects to firm characteristics, such as country or industry association. The extended empirical results on momentum are described in Section 2.4, in which the relation to the decomposition of Section 2.3 is indicated. This section also includes interaction of momentum with other firm-related characteristics such as industry, size, and turnover. In Section 2.5 we discuss several risk-based models that may explain why momentum profits exist, while possible behavioral explanations are analyzed in Section 2.6. Section 2.7 describes the profitability of momentum strategies after accounting for transactions costs. Finally, the conclusions are in Section 2.8.

2.2 Individual stock return momentum

The momentum effect is based on the idea that stocks with high returns in the recent past have higher future returns than stocks with low past returns. The momentum effect is typically defined as a positive relation between the return of a stock in a certain period with its lagged return, both relative to the cross-sectional sample mean. Note that the existence of momentum does not necessarily imply market inefficiency, since no asset pricing model has been assumed. See Section 2.5 for more details on risk-based explanations of the momentum effect. The definition of momentum can be represented by

$$\mathrm{E}\left\{\frac{1}{N}\sum_{i=1}^{N}\left(R_{i,t-1}-\overline{R}_{t-1}\right)\left(R_{i,t}-\overline{R}_{t}\right)\right\}>0, \tag{2.1}$$

with $R_{i,t}$ the return of stock i in period t, $\overline{R}_t$ the average return of the sample, and N the number of stocks.[6] An obvious estimator for this expectation is the sample analogue, averaging over all time periods t. We have used the index i above to denote individual stocks, but it can also be used to denote for example country or industry indices when momentum at the aggregate level is investigated, see Section 2.4.

Possibly inspired by the earlier results of DeBondt & Thaler (1985, 1987) and Lehmann (1990) on long and short-term reversals in stock returns, Jegadeesh & Titman (1993) examined medium-term return-based strategies. Their results indicate that a zero-investment portfolio with long-investment in stocks that performed well over the past 3–12 months continue to perform well over the next 3–12 months. They report an average excess re-

[6] To avoid confusion with time-series autocorrelation of a stock, we refrain from using the notation $Cov\{R_{i,t-1}, R_{i,t}\}$ for the cross-sectional covariance in (2.1), as is sometimes done is this line of literature.

Table 2.1: **Expected monthly excess returns on the market, size, value, and momentum portfolios, 1927-2002.** The notation is as follows: $RMRF$, market return in excess of the risk free rate; SMB, return differential between small and big market capitalization firms; HML, return differential between firms with high and low book-to-market ratios; UMD, return differential between firms with up and down returns over the month $t-12$ till $t-2$. The average returns are in percentages per month. The t-values are reported in square brackets and are corrected for possible autocorrelation in the returns on these factors.

Sample period	RMRF	SMB	HML	UMD
1927 – 2002	0.62	0.22	0.40	0.78
	[3.25]	[1.87]	[3.10]	[5.33]
1927 – 1941	0.45	0.40	0.15	0.47
	[0.65]	[1.02]	[0.31]	[0.78]
1942 – 1962	1.11	0.11	0.50	0.77
	[4.26]	[0.76]	[3.03]	[6.13]
1963 – 1989	0.41	0.27	0.50	0.80
	[1.57]	[1.45]	[3.12]	[4.45]
1990 – 2002	0.45	0.07	0.34	1.13
	[1.32]	[0.25]	[0.97]	[3.15]

turn on the (6,6) month strategy of 12 percent per annum, which is both statistically and economically significant. Initially, these results were received with skepticism. However, attributing momentum as a spurious result due to, for example, data-mining or methodological issues, seem unlikely after more than a decade of research in this field. Rouwenhorst (1998, 1999b) provides evidence indicating that momentum exists in many other stock markets, and Jegadeesh & Titman (2001) provide out-of-sample evidence for the US.

We analyze the magnitude and strength of the momentum effect by comparing the momentum returns to the three well-known risk factors from Fama & French (1993).[7] The estimation results are based on the sample 1927-2002, but subsamples are also analyzed for robustness. The overwhelming magnitude of the momentum results can be seen in Table 2.1. Over the full sample, the momentum effect is even stronger than the equity risk premium, both statistically and economically. With exception of the subperiod 1942-1962 the momentum strategy has earned higher returns (with higher t-values) than any of the risk factors from the established three-factor model. Note that these returns do not necessarily imply investor profits, as transactions costs have not been included yet.

[7] We use the US research returns data from the library of Kenneth French for this analysis. Note that the momentum strategy from this source is not directly comparable to Jegadeesh & Titman (1993), because it is a (11,1) strategy with one-month skip, with a control for size. For more detailed information, see French's website at `mba.tuck.dartmouth.edu/pages/faculty/ken.french/`.

Whereas the market index can be tracked at relatively low costs, momentum portfolios may require frequent trading. For a more detailed analysis on transactions costs, see Section 2.7 of this Chapter.

2.2.1 Stylized facts about the stock momentum effect

The initial analysis by Jegadeesh & Titman (1993) produced an excess return of 0.95 percent per month over the 1965–89 period on the six month momentum strategy, which has become the benchmark in more recent research on stock momentum. In addition, formation and holding periods ranging from three months to one year have been analyzed to exhibit momentum as well. In Table 2.2, the average excess returns on the six month strategy of some subsequent papers are reported. This table indicates that the momentum effect is present in each of the studies in this field. Nevertheless, the estimates of the magnitude of the effects differ across publications. While it is not always obvious what exactly drives the disparity in returns, we try to categorize the possible explanations in sample selection and research method differences.

The sample selection criteria are almost never identical. Jegadeesh & Titman (1993) already mention that momentum appears to be weak in the period prior to 1941, so studies using this period often find reduced momentum returns.[8] Other features that influence the outcomes are the inclusion of NASDAQ stocks into the analysis or stocks with low prices (below \$1 or \$5). Alternative selection procedures exclude stocks with smaller market capitalization than the NYSE lowest decile breakpoint, or require that other characteristics of the stocks are known before inclusion in the sample. Exclusion of low priced or small market capitalization stocks generally reduces the variability in portfolio returns, which leads to increased statistical significance. The fact that market value weighted strategies produce lower average returns than equally weighted strategies suggests that momentum is stronger for smaller stocks. The relation between the strength of momentum and firm size is described in more detail in Section 2.4. The momentum effect seems most pronounced in the extreme returns, since using top and bottom 20 or 30 percent of stocks generates lower average momentum returns than decile strategies. It is not fully clear to what extent the weighted relative strength strategy (WRSS) emphasizes extreme returns, as it takes long (short) positions in *each* stock above (below) the market average. In Section 2.2.2 the potential influence of weighting schemes is analyzed in more detail. Many papers report both a formation period contiguous with the holding period, and with a one week or one month skip between them. These skips between ranking and investment period should reduce market microstructure effects such as the bid-ask bounce and infrequent trading.

[8] This is consistent with Table 2.1, in which momentum is only weakly positive in the period before 1941.

Table 2.2: **US momentum returns reported in the literature.** In the first column the reference is made, and in the second and third we list the reported excess returns on winner minus loser (WML) strategies with corresponding t-values. The last three columns indicate the sample period, the weighting scheme, and the percentage of stocks in the portfolio. Note that for WRSS all stocks are used to calculate momentum profits, weighted by their relative return with respect to the market average.

Publication	WML	t-val	sample	wght	perc
Jegadeesh & Titman (1993)	0.95	3.07	1965–89	EW	10
Conrad & Kaul (1998)	0.36	4.55	1962–89	WRRS	
Moskowitz & Grinblatt (1999)	0.43	4.65	1973–95	VW	30
Lee & Swaminathan (2001)	1.05	4.28	1965–95	EW	10
Hong, Lim & Stein (2000)	0.53	2.61	1980–96	EW	30
Jegadeesh & Titman (2001)	1.23	6.46	1965–98	EW	10
Chordia & Shivakumar (2002)	1.51	6.52	1963–94	EW	10
Griffin, Ji & Martin (2003)	0.58	3.31	1927–00	EW	20

Skipping the first month seems to increase the returns somewhat, but the differences with standard (6,6) strategies are usually minor. Momentum strategies with shorter investment horizons are more prone to experience differences between the average returns on skip and non-skip strategies.

The apparent profitability of momentum strategies for the US stock market triggered many researchers to examine whether the same effect exists for international stock markets. Rouwenhorst (1998) investigates the existence of momentum effects for the European stock market, and finds a 1.16 percent (t-value 4.02) per month excess return of winners over losers on the (6,6) strategy over the period 1980–1995. Rouwenhorst also investigates the 12 European countries in his sample separately, and finds significant return continuation in 11 out of 12 countries.

Rouwenhorst (1999b) examines the momentum effect in 20 emerging markets over the period 1982–96. Although for only 6 countries statistically significant momentum is found, there appear to be just 3 countries with insignificant reversals. For the emerging markets as a whole, the reported excess return is 0.39 percent per month (t-value 2.68), while a cross-country average momentum strategy yields a 0.58 percent excess return (t-value 3.96). Griffin et al. (2003) report that emerging markets winners and losers have virtually the same returns over the period 1986–2000. In addition to differences in the sample period, this result might also be explained by the different set of countries in both papers.

In conclusion, the majority of papers claim the existence of stock return continuation at the individual stock level, although research on less developed equity markets seems to suffer from limited data availability.

2.2.2 Research methods to detect the momentum effect

The definition of stock return continuation or momentum can be formalized by equation (2.1). In order to investigate whether the momentum effect exists, several research methods have been proposed in the literature. These methods are designed to capture the momentum effect, but differ somewhat in their implementation, and hence might influence the empirical outcomes.

A first approach to detecting momentum effects is based on a sample analogue of the momentum effect of equation (2.1) and is often referred to as the weighted relative strength strategy (WRSS). This zero-investment portfolio has long positions in the stocks that outperformed the sample average, which are financed by short positions in the stocks which show and underperformance relative to the sample average. The portfolio weights depend linearly on the past return, $w_{i,t-1} = R_{i,t-1} - \overline{R}_{t-1}$, where $\overline{R}_{t-1}$ is the sample average return in period $t-1$. This allows us to write the average excess return of a WRSS as

$$\frac{1}{T}\sum_{t=1}^{T} R^e_{p,t} = \frac{1}{T \cdot N}\sum_{t=1}^{T}\sum_{i=1}^{N} w_{i,t-1}\left(R_{i,t} - \overline{R}_t\right). \tag{2.2}$$

Hence, the momentum effect can be estimated by calculating excess portfolio returns for the available time series of stock returns. The relevant hypothesis according to the definition in equation (2.1) is

$$\mathrm{H}_0 : \quad \mathrm{E}\{R^e_{p,t}\} = 0 \quad \text{vs} \quad H_1 : \quad \mathrm{E}\{R^e_{p,t}\} > 0,$$

or alternatively, a two-sided test in which the alternative is unequal to zero. A standard t-test can be carried out when the frequency of the return observations is equal to the holding period of the strategy. If longer holding periods are considered, there are at least three possibilities to proceed. First, the sample period can be split up in parts of with length equal to the holding period. This would lead to a test with relatively few observations, especially when longer horizon effects are investigated.

Second, one could also shift the six month period one month ahead each time. So whereas the first observation for both methods would be the same, the second observation would have formation and holding period shifted one month forward. This leads to more observations for the test, but these observations are not independent of each other. Hence, the test should be corrected for the overlapping samples that are used.[9] Intuitively, this means that we should take into account that the same stock return information is used more than once.

Third, we can use the method proposed by Jegadeesh & Titman (1993), in which

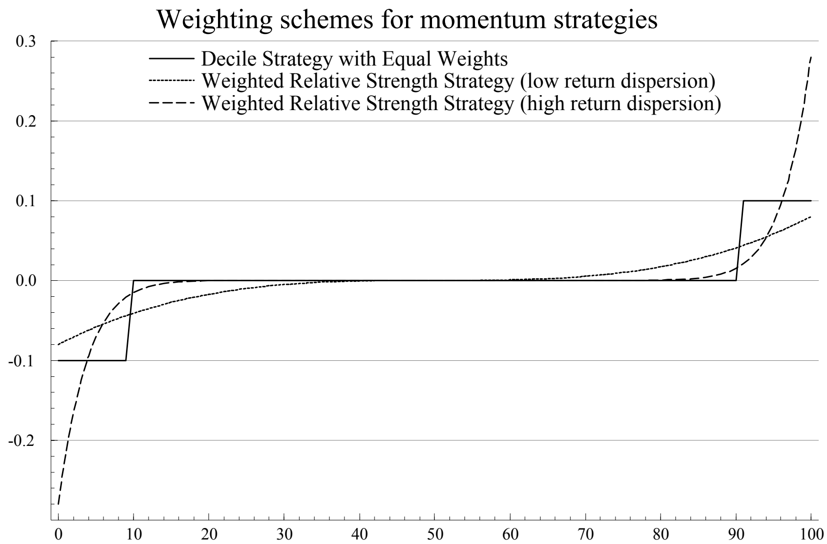
[9] A popular correction method for overlapping samples is described in Newey & West (1987).

portfolios are overlapping, but the returns are not. This involves ranking stocks on past returns each month, irrespective of the length of the holding period. In each month, the strategy consists of a portfolio selected in the current month, as well as *K-1* portfolios formed in the previous *K–1* months, with K the strategy's holding period. We refer to a strategy forming portfolios on past J month's returns and subsequently holds the portfolio for K months as a *(J,K)* strategy. Thus, each month, the total holding of a *(J,K)* strategy consists of K portfolios, one portfolio formed at the beginning of this month, and the other *K–1* are carried over from the previous months. This strategy does not suffer from the overlapping samples problem, but uses overlapping portfolios instead. Standard tests do not have to be corrected for serial correlation, assuming that there is no autocorrelation in monthly returns on the momentum portfolio.

A possible disadvantage of using the weights in equation (2.2) is the lack of robustness. Stocks that have outperformed (underperformed) the market by a large amount are dominant stocks in the momentum strategy, regardless of their market capitalization. Potentially, such WRSS could lead to long and short positions which contain only the smallest stocks listed, while the largest stocks hardly influence the excess return on the strategy. Implementation of a large portfolio to take advantage of the positive momentum return could lead to increased transactions costs, reducing the net expected return of momentum strategies. In addition, the large idiosyncratic components in WRSS portfolios might reduce reliable inference. In order to reduce the influence of these idiosyncratic returns, many papers use a step-wise weighting scheme in which the top 10 percent of the stocks in the ranking on past returns form the winner portfolio and the bottom 10 percent form the loser portfolio. An example of the differences in weighting schemes is shown in Figure 2.1. The WRSS strategy may have smooth weighting patterns, investing most in the stocks with the most extreme performances, whereas the decile strategy equally weights the top and bottom performers. This figure also shows the potential danger of using the WRSS strategy. With high cross-sectional return dispersion (dashed line), the stock weights reduce quickly when moving towards the middle of the sample. Stocks outside the top and bottom five only marginally contribute to the total momentum return. On the other hand, with low cross-sectional return dispersion the weights in stocks decrease slowly when moving towards the middle of the sample (dotted line), increasing the robustness of the decile strategy. Nevertheless, using a decile strategy has the advantage that extreme weighting schemes are excluded, and that portfolio weights of the stocks are equal throughout the analysis.

Alternative weighting schemes incorporating market value are used as well. Such strategy could select the top and bottom 10 percent of stocks in the past returns ranking, and use market value weights to determine the future return. The advantage of such strategy is that small stocks, which are typically expensive to trade, have a relatively

Figure 2.1: **Three potential weighting schemes for a momentum strategy.** This illustration assumes that the entire stock market consists of 100 stocks. On the horizontal axis the stocks are sorted on past return, with the most left (right) stock showing the worst (best) performance. The decile strategy equally weights 10 stocks in the loser and 10 stocks in the winner portfolio. The total long (short) portfolio adds to 100 (-100) percent. The dotted line shows the weighted relative strength strategy if the return dispersion is low. More stocks enter the strategy, but the weights slowly decrease moving towards the middle. The dashed line shows the same weighting scheme, but now with high return dispersion. Stocks with extreme stock returns are dominant in the momentum portfolio.



small weight in the momentum portfolio.

The set of strategies proposed by Jegadeesh & Titman (1993), in which overlapping portfolios instead of overlapping returns are used to measure the momentum effect, can be rebalanced monthly. The choice to rebalance these portfolios might influence the reported excess returns on longer holding periods, typically leading to somewhat lower returns for monthly rebalanced strategies.

The portfolio formation techniques as described above are used to investigate many hypotheses in finance. The reason why this approach is used is probably because of its intuitive appeal. The method provides an average return that the investor would have realized given a portfolio selection criterion, possibly including transactions costs. We show that these portfolio formation techniques can be interpreted as special cases of traditional regression models for panel data.

The regression equation for the panel of stocks is

$$Y_{i,t} = \beta \cdot X_{i,t} + \varepsilon_{i,t}, \tag{2.3}$$

where β is vector of unknown parameters that have to be estimated using data $Y_{i,t}$ and $X_{i,t}$ for stocks $i = 1, ..., N$ and time $t = 1, ..., T$. Suppose now that

- $Y_{i,t}$ is the excess return of stock i in period t (excess with respect to the average return of all stocks at period t).
- $X_{i,t}$ is the excess return of stock i in period $t-1$ (excess with respect to the average return of all stocks at period $t-1$).

The numerator of the OLS-estimate of β equals the sample analogue of equation (2.1). Thus, with appropriate restrictions on the covariance structure of the error terms $\varepsilon_{i,t}$, this regression equation can be used to test whether the null hypothesis of 'no momentum' can be rejected. Note that when the number of stocks changes over time, which is generally the case, N should be replaced by N_t.

Alternatively, the decile sorting procedure can also be written in a regression context. In this setup, inference from the equally weighted (EW) sorting procedure and the regression model in equation (2.3) is obtained when

- $Y_{i,t}$ is the return of stock i in period t.
- $X_{i,t}$ is a set of D dummy variables indicating in which group stock i was on the basis of ranking in period $t-1$.

The interpretation of the D unknown coefficients in β is the expected return from being in a certain group of stocks in the previous ranking period. We will show that the Fama-MacBeth estimator of β coincides with the estimates attained from the portfolio formation approach discussed above.[10] This Fama-MacBeth estimator consists of two steps. First, a cross-sectional regression is estimated for each t, resulting in a time-series of parameter estimates $\widehat{\beta}_t$, which is the same as computing the average return of the group of stocks at time t. Second, the estimator for β is the time-series average of these cross-sectional estimates. As the cross-sectional estimates are assumed to be independent observations, the variance matrix of this estimator can be obtained by the empirical variance of the time-series $\widehat{\beta}_t$. This corresponds to taking the time-series average returns on the portfolios and calculating the variance of the returns of the long-short portfolio. Thus, these two steps from the Fama-MacBeth estimator correspond to the usual practice of first calculating average portfolio returns, and then averaging these portfolio returns over time. Note that we implicitly condition on the whole sample of stocks by conditioning on $X_{i,t}$ as the dummies are constructed by a ranking procedure. Applying weighted least squares (WLS)

[10] See Fama & MacBeth (1973) for the introduction of this estimator.

instead of ordinary least squares (OLS) in the cross-sectional regressions of the first step allows the implementation of value weighting (VW) instead of EW.

The advantage of the ranking (sorting) method is its intuitive interpretation, but on the downside, much information about the stock characteristics in the sample is not exploited. The expected returns of two stocks on both sides of a decile are completely unrelated using such weighting scheme. Especially for the simultaneous investigation of a multitude of effects by multiple sorting, the number of stocks per portfolio may be dramatically reduced. In Chapter 4 a novel portfolio-based regression approach is used to disentangle country, industry, and individual momentum effects in Europe, while allowing for possible nonlinear interaction effects. We regress the return of a set of basis portfolios on the holdings of these portfolios in a multitude of categories, such as momentum, size, and value. In the special case that the set of basis portfolios only consists of momentum portfolios, and that the investigated category is just momentum, the holdings reduce to dummies and the usual sorting results are obtained.

2.3 A decomposition of the momentum effect

In order to provide insight into the determinants of the momentum effect we decompose the cross-section of stock returns. The decomposition as presented here is based on Lo & MacKinlay (1990b). Extensions by Moskowitz & Grinblatt (1999) and Chan, Hameed & Tong (2000) allow separation between industry or country dimensions in momentum returns, including foreign exchange effects that might play a role. Reinterpreting these extended models allows for country and industry momentum simultaneously. Recall the definition of the momentum effect from equation (2.1),

$$\mathrm{E}\left\{\frac{1}{N}\sum_{i=1}^{N} w_{i,t-1}\left(R_{i,t}-\overline{R}_t\right)\right\} > 0,$$

where $w_{i,t-1} = R_{i,t-1} - \overline{R}_{t-1}$. Conrad & Kaul (1998) assume a random walk with drift for stock prices. The unconditional expected return of stock i, $\mathrm{E}\{R_{i,t}\}$, is denoted by μ_i. Deviations from this expectation are captured by an idiosyncratic term $\varepsilon_{i,t}$, with unconditional expectation $\mathrm{E}\{\varepsilon_{i,t}\} = 0$. Contemporaneous covariance with other stocks is allowed, i.e., Conrad & Kaul do not assume $\mathrm{E}\{\varepsilon_{i,t}\varepsilon_{j,t}\} = 0$, but serial (cross) correlation is assumed to be absent, $\mathrm{E}\{\varepsilon_{i,t}\varepsilon_{j,t-1}\} = 0$ for all i and j. The return generating process of stock i can now be written as

$$R_{i,t} = \mu_i + \varepsilon_{i,t}. \tag{2.4}$$

In the absence of serial (cross) correlation, momentum profits are only driven by cross-sectional dispersion in expected returns. Plugging the return generating process of equation (2.4) into equation (2.1), the momentum return for period t can be written as

$$\mathrm{E}\left\{\frac{1}{N}\sum_{i=1}^{N} w_{i,t-1}\left(R_{i,t}-\overline{R}_t\right)\right\} = \frac{1}{N}\sum_{i=1}^{N}\left(\mu_i-\overline{\mu}\right)^2,$$

where $\overline{\mu} = \frac{1}{N}\sum_{j=1}^{N}\mu_j$. Conrad & Kaul's (1998) hypothesis states that the dispersion in unconditional expected stock returns explains momentum, and they provide empirical evidence supporting their conjecture. Jegadeesh & Titman (2001) show that this hypothesis implies that momentum returns should increase linearly with the holding period. Jegadeesh & Titman claim that there is little empirical evidence confirming this prediction following from the hypothesis of Conrad & Kaul (1998).

The assumption that cross-correlations in individual stock returns are zero, i.e. $\mathrm{E}\{\varepsilon_{i,t}\varepsilon_{j,t-1}\} = 0$ for $i \neq j$, may be restrictive. Lewellen (2002) relaxes this assumption in order to create a decomposition of momentum returns. Lewellen's decomposition for the momentum return is

$$\frac{1}{N}\sum_{i=1}^{N} w_{i,t}(R_{i,t}-\overline{R}_t) = \sigma_\mu^2 + \frac{N-1}{N^2}\sum_{i=1}^{N}\varepsilon_{i,t-1}\varepsilon_{i,t} - \frac{1}{N^2}\sum_{i=1}^{N}\sum_{j\neq i}^{N}\varepsilon_{j,t-1}\varepsilon_{i,t},$$

with $\sigma_\mu^2 = \frac{1}{N}\sum_{i=1}^{N}\left(\mu_i-\overline{\mu}\right)^2$. The empirical work of Lewellen (2002) indicates that these (negative) cross-covariances are causing the momentum effect, rather than the stock's autocorrelation from the second term, as argued in, e.g., Jegadeesh & Titman (1993).[11]

Jegadeesh & Titman (1993) assume that stocks can be priced by a single factor, which can be thought of as the market return in the Capital Asset Pricing Model (CAPM). The unconditional expected stock return for period t can be written as

$$\mu_i = R^f + \beta_i \cdot \mathrm{E}\{R^e_{m,t}\},$$

with R^f the return on the riskfree asset, $R^e_{m,t}$ the excess return of the market over the riskfree rate, and $\beta_i = \frac{\mathrm{Cov}\{R_{i,t},R_{m,t}\}}{\mathrm{Var}\{R_m\}}$. The error term $\varepsilon_{i,t}$ is decomposed in a factor component and a stock-specific component $\eta_{i,t}$,

$$\varepsilon_{i,t} = \beta_i \cdot (R^e_{m,t} - \mathrm{E}\{R^e_{m,t}\}) + \eta_{i,t}.$$

Jegadeesh & Titman assume that $\mathrm{E}\{\eta_{i,t}\} = 0$, $\mathrm{E}\{\eta_{i,t}R^e_{m,t}\} = 0$, $\mathrm{E}\{\eta_{i,t}R^e_{m,t-1}\} = 0$, and

[11] These cross-effects could be interpreted as overreaction by investors to news in other firms. A higher firm-specific return of firm j in period $t-1$ would lead to a lower return of firm i in period t. In Cheng & Hong (2002), it is argued that the empirical results of Lewellen (2002) need not imply investor overreaction, but can also be consistent with a model based on underreaction behavior.

$\mathrm{E}\{\eta_{j,t}\eta_{i,t-1}\} = 0$ for $i \neq j$. The return generating process for stocks can now be written as

$$R_{i,t} = \mu_i + \beta_i \cdot \widetilde{R}^e_{m,t} + \eta_{i,t}, \tag{2.5}$$

where $\widetilde{R}^e_{m,t} = R^e_{m,t} - \mathrm{E}\{R^e_{m,t}\}$. If the stock returns of equation (2.5) are substituted in equation (2.1) the decomposition for momentum returns in period t is

$$\frac{1}{N}\sum_{i=1}^{N} w_{i,t-1}\left(R_{i,t} - \overline{R}_t\right) = \sigma^2_\mu + \sigma^2_\beta \mathrm{Cov}\{\widetilde{R}^e_{m,t-1}, \widetilde{R}^e_{m,t}\} + \frac{1}{N}\sum_{i=1}^{N} \eta_{i,t-1}, \eta_{i,t},$$

where $\sigma^2_\beta = \frac{1}{N}\sum_{i=1}^{N}\left(\beta_i - \overline{\beta}\right)^2$, with $\overline{\beta} = \frac{1}{N}\sum_{j=1}^{N}\beta_j$. The expected momentum return is split in three parts. The first part is due to the dispersion in unconditional expected returns, which is the driving factor according to Conrad & Kaul (1998). The second part is the dispersion in factor exposures times the autocovariance in the excess market return. The last factor is autocorrelation in idiosyncratic stock returns. Jegadeesh & Titman (1993) conclude that autocorrelation in idiosyncratic returns is driving the momentum effect, but their results might be spuriously generated because of the restriction that $\mathrm{E}\{\eta_{i,t}\eta_{j,t-1}\} = 0$. A straightforward extension is to assume a multi-factor model explaining the cross-section of stock returns, e.g., the three-factor model of Fama & French (1993). Assuming that these factors are not cross-autocorrelated, i.e., $Cov\{\widetilde{R}^e_{k,t-1}, \widetilde{R}^e_{l,t}\} = 0$ for $k \neq l$, the decomposition consists now of a sum of the product of exposure dispersions $\sigma^2_{\beta_k}$ and factor autocovariances $\mathrm{Cov}\{\widetilde{R}^e_{k,t-1}, \widetilde{R}^e_{k,t}\}$.

Moskowitz & Grinblatt (1999) claim that, in addition to the risk factors mentioned above, industry related factors might explain the residual error $\eta_{i,t}$ even further. They assume that $\eta_{i,t} = \sum_{l=1}^{L}\theta_{i,l}\cdot\widetilde{R}^z_{l,t} + \nu_{i,t}$, leading to a stock return generating process of the following form

$$R_{i,t} = \mu_i + \sum_{k=1}^{K}\beta_{i,k}\cdot\widetilde{R}^e_{k,t} + \sum_{l=1}^{L}\theta_{i,l}\cdot\widetilde{R}^z_{l,t} + \nu_{i,t}, \tag{2.6}$$

where industry factors $\widetilde{R}^z_{l,t}$ are orthogonalized with respect to the risk factors $\widetilde{R}^e_{k,t}$. These factors can be reinterpreted as country factors in an international context.[12] When we assume additivity of country and industry effects, as is also done in for example Heston & Rouwenhorst (1994), L_1 components of $\widetilde{R}^z_{l,t}$ can be seen as country factors and L_2 components as industry factors. The factor is now remodeled to

$$\sum_{l=1}^{L}\theta_{i,l}\cdot\widetilde{R}^z_{l,t} = \sum_{l=1}^{L_1}\theta_{i,l}\cdot\widetilde{R}^z_{l,t} + \sum_{l=L_1+1}^{L_1+L_2}\theta_{i,l}\cdot\widetilde{R}^z_{l,t}. \tag{2.7}$$

[12]Numerous papers have investigated the relative importance of countries versus industries; see e.g. Roll (1992) or Heston & Rouwenhorst (1994).

The assumption of additive country and industry effects might be restrictive, and can be relaxed by allowing the $\widetilde{R}^z_{l,t}$-s to represent country-industry specific factors.[13] Extending the model with currency effects can be done in a similar fashion. The decomposition of country momentum in Chan et al. (2000) and Bhojraj & Swaminathan (2001) allow, next to stock and currency momentum also for cross-autocorrelations between stocks and currencies,

$$\begin{aligned}
&\mathrm{E}\left\{\frac{1}{N}\sum_{i=1}^{N}(R_{i,t-1}-\overline{R}_{t-1})(R_{i,t}-\overline{R}_t)\right\} = \\
&\quad \mathrm{E}\left\{\frac{1}{N}\sum_{i=1}^{N}(r_{i,t-1}-\overline{r}_{t-1})(r_{i,t}-\overline{r}_t)\right\} + \mathrm{E}\left\{\frac{1}{N}\sum_{i=1}^{N}(e_{i,t-1}-\overline{e}_{t-1})(r_{i,t}-\overline{r}_t)\right\} + \\
&\qquad + \mathrm{E}\left\{\frac{1}{N}\sum_{i=1}^{N}(r_{i,t-1}-\overline{r}_{t-1})(e_{i,t}-\overline{e}_t)\right\} + \mathrm{E}\left\{\frac{1}{N}\sum_{i=1}^{N}(e_{i,t-1}-\overline{e}_{t-1})(e_{i,t}-\overline{e}_t)\right\},
\end{aligned}$$

where $r_{i,t}$ denote local returns, $e_{i,t}$ denote exchange rate returns, $\overline{e}_t = \frac{1}{N}\sum_{i=1}^{N} e_{i,t}$, and where we use the approximation $R_{i,t} \approx r_{i,t} + e_{i,t}$. The first term of this decomposition can be decomposed as, e.g., in equation (2.6), and the latter three are related to exchange rate effects.

Summarizing, the return decomposition of international stock momentum portfolio can be written as

$$\begin{aligned}
\frac{1}{N}\sum_{i=1}^{N} w_{i,t-1}(R_{i,t}-\overline{R}_t)\} &= \sigma^2_\mu + \sum_{k=1}^{K}\sigma^2_{\beta_k}\mathrm{Cov}\{\widetilde{R}^e_{k,t-1},\widetilde{R}^e_{k,t}\} + \sum_{l=1}^{L}\sigma^2_{\theta_l}\mathrm{Cov}\{\widetilde{R}^z_{l,t-1},\widetilde{R}^z_{l,t}\} + \\
&\quad + \frac{1}{N}\sum_{i=1}^{N}\left[\widetilde{e}_{i,t-1}(r_{i,t}-\overline{r}_t) + (r_{i,t-1}-\overline{r}_{t-1})\widetilde{e}_{i,t} + \widetilde{e}_{i,t-1}\widetilde{e}_{i,t}\right] + \\
&\quad + \frac{N-1}{N^2}\sum_{i=1}^{N}\nu_{i,t-1}\nu_{i,t} - \frac{1}{N^2}\sum_{i=1}^{N}\sum_{j\neq i}^{N}\nu_{j,t-1}\nu_{i,t}, \qquad (2.8)
\end{aligned}$$

where $\widetilde{e}_{i,t} = e_{i,t} - \overline{e}_t$. Note that the L factors on the first line can be further split up into, for example, country and industry factors. The assumptions used to obtain the

[13] Using country-industry specific effects yields $L_1 \times L_2$ components instead of $L_1 + L_2$ when additivity is assumed. In Chapter 4 we present a portfolio-based regression method to allow for interaction effects between industries and countries. Moreover, they describe a test to investigate the importance of the cross-effects.

decomposition in equation (2.8) are

$$
\begin{array}{llll}
\mathrm{E}\{R^e_{j,t}R^e_{k,t-1}\} = 0 & \forall j \neq k & \mathrm{E}\{R^z_{n,t}R^z_{m,t-1}\} = 0 & \forall n \neq m \\
\mathrm{E}\{R^e_{k,t}R^z_{m,t-1}\} = 0 & \forall k, m & \mathrm{E}\{R^z_{m,t}\nu_{i,t-1}\} = 0 & \forall m, i \\
\mathrm{E}\{R^e_{k,t}\nu_{i,t-1}\} = 0 & \forall k, i & &
\end{array}
$$

The decomposition in equation (2.8) states that momentum can be driven by several factors. The factors on the first line are cross-section dispersion in expected returns, autocorrelation in risk factors, and autocorrelation in returns on country or industry factors. On the second line it is indicated that the interaction of stock returns with exchange rate movements may be important for momentum across equity markets. The third line in equation (2.8) shows that autocorrelation in individual stock returns or cross-correlation between these idiosyncrasies might drive return continuation. The empirical importance of these factors are investigated in studies that we discuss below in more detail. Knowledge about the driving forces behind the momentum effect might increase our understanding of the momentum effect and provide guidance for the evaluation of theoretical models.

2.4 Momentum and stock characteristics

Instead of focussing on individual stock momentum, several studies focus on the momentum effect while first grouping stocks on firm characteristics, such as country, industry, size, or value. In this subsection we describe these studies in more detail.

Richards (1997) investigates momentum and contrarian strategies at the country index level, and concludes that the momentum effect of 0.57 percent per month at the six month horizon is statistically insignificant. Chan et al. (2000) on the other hand, find a significant excess momentum return of 0.46 percent per month (t-value 2.35). This difference could be explained by a different sample period, a different set of countries, and different portfolio construction, but it is impossible to determine the exact cause without further investigation. Bhojraj & Swaminathan (2001) confirm the qualitative results by Chan et al. (2000), suggesting that momentum on a country level exists. They find significant excess returns for their total sample of 38 countries, as well as the subsample with only 16 developed countries. They document that ranking countries on their local return improves a momentum industry on the country index level. These papers estimate the momentum effect using countries as the investable assets, possibly including exchange rate effects as indicated in above. An alternative would be to examine equation (2.8) at the individual stock level and determine whether the country component is important in the decomposition of the total momentum effect.

Moskowitz & Grinblatt (1999) claim that the momentum effect can be explained solely by momentum in industry returns. This means that the third component in equation (2.8) drives the total momentum effect. They report that after correcting for industry effects, return continuation disappears. Several other studies have investigated their claim, but come to a different conclusion. For example, Lee & Swaminathan (2001) indicate that correcting for industries weakens the individual momentum results from 12.5 to 10.1 percent per annum, implying only a decline of 20 percent. Grundy & Martin (2001) indicate that industry momentum captures only half the size of the individual momentum effect. It seems that skipping the first month after portfolio formation and using 30% percent of the stocks in the winner and loser portfolio instead of 10% is crucial for the claims of Moskowitz & Grinblatt. Lewellen (2002) and Chordia & Shivakumar (2002) also find significant industry momentum, but the individual momentum effect is still present in their sample after controlling for industry momentum. In Chapter 3, we find empirical evidence for the existence of industry momentum in Europe, but not for the Japanese stock market.

In Chapter 4 we investigate country, industry, and individual stock momentum effects for the European stock market simultaneously. We aim to separate country and industry components, as described in equation (2.7). Our results suggest that the individual momentum effect is most pronounced, followed by industry momentum, while country momentum is virtually nonexistent. We find further that interaction effects with size and value are important in combination with momentum. In particular, our results indicate that momentum is most pronounced for small growth stocks. The results on the relative importance of country, industry, and individual stock factors are unaffected by the inclusion of size and value.

Next to an industry classification, Lewellen (2002) uses also size, value, and size-value sorted portfolios as investable assets. Lewellen reports medium term return continuation for all these classifications using WRSS portfolios. From these results Lewellen concludes that the momentum effect cannot be attributed to momentum in firm- or industry-specific returns.

The relation of return momentum to other firm characteristics has intrigued several researchers. In Jegadeesh & Titman (1993, 2001), momentum is investigated for different size groups. In the first paper, they divide their sample in three subsamples based on firm market value, and form momentum portfolios. They obtain significant excess returns for each of the three subsamples. In the latter paper, Jegadeesh & Titman divide their sample into small and large cap, based on the medium NYSE market capitalization. They find that the momentum effect is more pronounced for small cap stocks. Note that in the latter paper also NASDAQ stocks are included, but the smallest decile (based on NYSE stocks), together with stocks that quote below $5, are deleted from their sample. They exclude these stocks because they are afraid that illiquid stocks might drive their earlier findings. Hong et al. (2000) investigate the relation between momentum and size in more detail. Hong et al. examine the momentum effect by dividing the sample in three momentum portfolios instead of ten. Most papers find that momentum is more pronounced for extreme stock returns, which might reduce the strength of Hong et al.'s results. Nevertheless, they find that momentum is non-existent in the 30 percent stocks with highest market value.[14] For the smallest decile, which is excluded in Jegadeesh & Titman (2001), they report return reversals instead of momentum. The weaker momentum effect for value-weighted momentum portfolios instead of equally weighted portfolios is also an indication that large stocks exhibit less momentum; see for example Moskowitz & Grinblatt (1999) who find 9.3 and 5.2 percent per annum for equally and value weighted momentum tertile portfolios, respectively. In an international context, Rouwenhorst (1998) finds that for his European sample the momentum effect is somewhat stronger for small stocks, confirming the findings of Jegadeesh & Titman.

Chan, Jegadeesh & Lakonishok (1996) investigate the relationship between earnings and price momentum strategies. They find that, using three measures of unexpected earnings, earnings momentum is present. These three measures are standard unexpected earnings (defined as the scaled earnings change relative to the same quarter in the previous year), the abnormal return around the earnings announcement, and the moving average of analyst revisions. The results from their two-way analysis suggests that earnings momentum and price momentum are two different phenomena.

Lee & Swaminathan (2001) investigate the relation between trading volume and momentum in more detail.[15] They indicate that stocks with high past turnover exhibit stronger momentum effects than stocks with low past turnover. In addition, they define *early* and *late* stage momentum strategies. Early stage momentum refers to buying low volume winners and selling high volume losers, while the late stage momentum strategy refers to buying high volume winners and selling low volume losers. The early stage strategy has substantially higher returns over the past first year, 16.7 percent versus 6.8 percent per annum for the late stage strategy, and dissipates slower in the years after.

[14] Since most institutional investors are confined to invest in this group of stocks, for them the presence of momentum in these large cap stocks would be most relevant. In addition, Hong et al. (2000) also examine the relation between analyst coverage and momentum, and find that the momentum effect is stronger for firms with low analyst coverage, even when controlling for firm size.

[15] The relation between trading volume and momentum for the German stock market is analyzed in similar fashion by Glaser & Weber (2003). They confirm the hypotheses from Lee & Swaminathan that momentum is more pronounced for stocks with much turnover.

2.5 Risk-based explanations for momentum

Jegadeesh & Titman (1993) already try to explain momentum as a reward for risk. They investigate whether the excess returns generated by the momentum strategies can be due to a positive CAPM beta in the zero-investment momentum strategy. However, their results suggest that differences in market risk do not cause momentum profits. Fama & French (1996) fail to price the momentum profits by exposures to the risk factors in the three-factor unconditional asset pricing model by Fama & French (1993). Their results are confirmed by Jegadeesh & Titman (2001), who claim that risk-corrections more likely increase the momentum returns than decrease due to the negative exposures to the size and value factor of the momentum portfolios.

As the decomposition in equation (2.8) shows, momentum profits are potentially explained by the cross-sectional dispersion in unconditional expected returns, σ_μ^2, or conditional risk factors. If the exposures to the risk factors of each stock are known, sorting can take place on the pricing errors instead of raw returns. A risk-based explanation is rejected if these sorts on pricing errors still exhibit momentum. Of course, rejecting risk-based explanations might also be caused by a failure to identify the relevant risk factors. Ang, Chen & Xing (2001) construct a factor capturing downside risk and find that part, but not all, of the momentum effect can be explained by a positive loading of the winner minus loser portfolio to this new factor.

Exposures to risk-factors are in general unknown, and can be hard to estimate, especially at the individual stock level. It is common practice to first rank the stocks on raw returns and estimate the risk exposures after portfolio formation. When we denote the excess returns on the momentum portfolio R_t^{wml}, the excess market return R_t^{mkt}, the size factor R_t^{smb}, and the value factor R_t^{hml}, the regression equation used to investigate these unconditional pricing models is

$$R_t^{wml} = \alpha + \beta \cdot R_t^{mkt} + s \cdot R_t^{smb} + h \cdot R_t^{hml} + \varepsilon_t, \tag{2.9}$$

where β, s, and h are the risk exposures of the excess returns on the up minus down or winner minus loser portfolios. The asset pricing model predicts that the constant α is zero in this regression. This null hypothesis is rejected in, e.g., Fama & French (1996) and Jegadeesh & Titman (2001).

In a recent paper, Wu (2002) claims that a conditional version of the three-factor model in equation (2.9) is able to price momentum portfolios. Wu explicitly models time-variation in risk exposures by adopting the method introduced by Shanken (1990).[16] The

[16] For alternative ways to incorporate time-variation in risk exposures, see Chapters 7 and 8 of this thesis.

regression model changes to

$$R_t^{wml} = \alpha + M_{t-1}\gamma_m R_t^{mkt} + M_{t-1}\gamma_s R_t^{smb} + M_{t-1}\gamma_h R_t^{hml} + \varepsilon_t, \tag{2.10}$$

where M is a vector of macro economic variables (including a constant) and γ_m, γ_s, and γ_h capture the (linear) dependency of the macro economic variables to the risk exposures. Wu finds overwhelming empirical evidence supporting the conditional exposure approach, since the parameters γ for the macro economic sensitivities are statistically significant. In contrast to the *unconditional* findings of, e.g., Fama & French (1996), Wu finds that *conditional* risk exposures of winners and losers are negatively cross-correlated, indicating that winners and losers have different conditional exposures to risk factors. However, this approach cannot explain the momentum profits completely, since the null hypothesis that α equals zero is still rejected using this model.

In contrast to explicitly modeling time-variation in the risk-exposures to unconditionally priced risk factors, the risk premia themselves might be time-varying. Recall the stock generating process in equation (2.5),

$$R_{i,t} = \mu_i + \beta_i \cdot \widetilde{R}^e_{m,t} + \eta_{i,t},$$

with assumptions $\mathrm{E}\{\widetilde{R}^e_{m,t}\} = 0$, $\mathrm{E}\{\eta_{i,t}\} = 0$, and $\mathrm{E}\{\eta_{i,t}\widetilde{R}^e_{m,s}\} = 0$ for $s = t, t-1$. If we now assume that the risk premium can be modeled as

$$\mathrm{E}\{\widetilde{R}^e_{m,t}|M_{t-1}\} = \delta M_{t-1},$$

the conditional expected stock return equals

$$\begin{aligned} \mathrm{E}\{R_{i,t}|M_{t-1}\} &= \mu_i + \beta_i \mathrm{E}\{\widetilde{R}^e_{m,t}|M_{t-1}\} + \mathrm{E}\{\varepsilon_{i,t}|M_{t-1}\} \\ &= \mu_i + \gamma_i M_{t-1}, \end{aligned}$$

where $\gamma_i \equiv \beta_i \delta$.[17] Wu (2002) examines a similar specification where the prices of risk are modeled as linear functions of the macro economic variables without assuming constant risk exposures, and estimates the corresponding moment restrictions by GMM. He finds empirical evidence in favor of time-varying risk premia. As opposed to the model with a linear relationship between the exposures and lagged economic variables, this conditional model with time-varying risk premia can explain momentum profits. However, this model does not allow much insight in the conditional risk exposure of the momentum portfolio to these risk factors, as the risk exposures are not identified in this model.

[17]Note that we assume here that the macro economic variable M is such that its unconditional expectation equals zero.

A related paper by Chordia & Shivakumar (2002) uses the same idea but a slightly different methodology to investigate the influence of time-variation in risk-premia on momentum profits. They estimate the regression equation

$$R_{i,t} = \alpha_i + \beta_i M_{t-1} + \varepsilon_{i,t} \tag{2.11}$$

for each stock i and use the estimated coefficients $\widehat{\alpha}_i$ and $\widehat{\beta}_i$ to predict the stocks return in the next period, i.e., $\widehat{R}_{i,t+1} = \widehat{\alpha}_i + \widehat{\beta}_i M_t$.[18] They subsequently sort the stocks on these predicted returns and find that within groups with similar return prediction the excess returns of momentum strategies are substantially reduced. On the basis of this result Chordia & Shivakumar conclude that momentum profits can be attributed to higher conditional expected returns, and is thus a compensation for bearing macro economic risks.

Griffin et al. (2003) also investigate whether momentum profits around the world can be attributed to macro-economic risks by using the Chen, Roll & Ross (1986) approach. Thus, Griffin et al. regress the momentum returns on contemporaneous macro economic variables,

$$R_t^{wml} = \alpha + \beta' M_t + \varepsilon_t. \tag{2.12}$$

In this setup the Fama & French (1993) risk factors are replaced by macro economic variables. The tests of Griffin et al. on the intercept suggest that there is no relation between macro economic risks and momentum profits. They furthermore cast doubt on the economic interpretation of the results reported by Chordia & Shivakumar (2002). Griffin et al. claim that the results of Chordia & Shivakumar are based on a return prediction model with low explanatory power. Average adjusted R^2-s are about 5 percent, which makes the predictions particularly vulnerable to the set of macro variables included in the prediction model.

In addition to these empirical papers, Johnson (2002) develops a theoretical model without using irrational or heterogeneous investors, or market frictions such as transactions costs. Johnson makes use of occasional persistent dividend growth rate shocks to explain momentum on a rational basis.

Summarizing, the empirical results for a risk-based explanation for the existence of momentum are mixed. While traditional unconditional pricing models are unable to explain the excess returns on momentum strategies, there is some evidence that models with time-varying risk premia can provide a risk-based explanation for the existence of the momentum effect. Hence, these conditional models require an increased number of parameters and hence explanations might be spurious. In conclusion, there is no widespread

[18] The ommission of the time subscript in the notation is for notational convenience only. The exposures in the model are estimated using a 60-month rolling window and hence are allowed to be different for each period t. Thus implicitly also time-variation in the β-s is allowed in this model.

agreement that excess momentum returns are a trivial and well-understood compensation for bearing exposure to higher risk.

2.6 Behavioral explanations for momentum

The lack of straightforward risk-based explanations of the momentum effect has lead to research papers in which the trading behavior of investor is analyzed in further detail. Several anecdotal examples challenging the often-assumed fully rational behavior of investors have recently been put forward to motivate research in this field. Apparent irrational behavior might be due to psychological factors underlying the human decision making process, or because different investor types have different information sets on which they condition their trading decisions.

The development of a behavioral model that describes a single artifact in the data by irrational trading behavior does in itself not provide much new insights, as the assumed behavior might be molded such that the outcome fits with the observed trading data. Therefore, at least three aspects of behavioral models should be evaluated separately. These three aspects are described before we analyze several behavioral models that try to explain momentum.

Firstly, the assumed investor behavior should be plausible and derived from known behavioral patterns in psychology or related fields. Systematic biases such as overconfidence or conservatism are well known in certain psychological settings, and could therefore potentially affect stock market prices as a whole. Temporary deviations from fundamental values may appear because arbitrageurs cannot always fully exploit irrational behavior.

Secondly, other stylized facts from market price dynamics should also fit with the predictions from the behavioral models. For example, a behavioral model that also explains the value effect is stronger than a model that is only able to capture momentum returns. Other established stylized facts about market volatility or covariance should preferably also be explained by the model.

Finally, the model should make predictions about observable features of the stock market that have not yet been established. These predictions should be tested empirically in order to evaluate the assumptions of the model. These "out of sample" tests prevent model-mining, i.e. tweaking the model for investor behavior until it matches the observed data.[19]

[19] The reservations on acceptance of behavioral models are analogous to the data-mining (or data-snooping) accusations that theoretically unfounded empirical work often suffers from. Model-mining refers to the search for theoretical models until these assumptions on behavior lead to the observed data, while data-mining refers to the widespread empirical search for anomalies or return predictability that appear to be statistically significant violations against theoretical models.

In Daniel et al. (1998) investors overestimate their own abilities, which is a known behavioral bias in psychological experiments. For example, people tend to systematically overestimate their driving skills. In the context of financial markets, investors are overconfident in their private signals related to the value of a firm, but not about publicly announced news about the firm value. In addition, investors do not update the confidence in their own skill rationally. If subsequent market movements confirm a trade decision, investors increase the belief in their ability, while they attribute adverse market movements to external factors. This way, the arrival of public news on average increases the confidence of the investor in his private information. This induces overconfident investors to trade more aggressively on their private information than what is fully rational. The noisy information that becomes available through public announcements is not recognized immediately, but it takes a while before this information is included in the stock price.

The model of Daniel et al. (1998) is a single agent model with irrational behavior of investors, causing initial overreaction based on overconfidence on private information and subsequent reversals because investors underreact to public signals about the firm value. Momentum is explained by positive autocorrelation of stock returns in the short run through continued overreaction. Underreaction of stocks prices to public news introduces reversals documented by, e.g., DeBondt & Thaler (1985).

Barberis et al. (1998) use other psychological behavior as Daniel et al. (1998) which can also explain stock return continuation on the short run and reversals on the long run. Their model of investor sentiment argues that underreaction instead of overreaction causes momentum. Investor behavior is in their model characterized by representativeness and conservatism. Conservatism relates to slow updating of beliefs when new evidence is presented. Representativeness means that investors classify the outcome of some stochastic variable as typical for a certain class, without analyzing the probabilities associated with the process. For example, in their paper the firm's earnings follow a random walk, but investors think it is either mean-reverting or trending. They update their information about the state by observing earnings news data and increase their subjective probability about the state in each period. However, investors emphasize the strength of earnings announcements and forget about the statistical weight associated with this news. Low strength but statistical significance causes them to underreact to news about earnings, but a series of statistically insignificant good (or bad) news events causes them to overreact on earnings news.

The model of Barberis et al. (1998) shares many features with the model of Daniel et al. (1998), as it is also a single agent model with irrational agents updating their beliefs in a Bayesian manner. However, Barberis et al. claim that underreaction causes momentum, whereas Daniel et al. use a different set of psychological insights to derive that investors overreact to news. It is not ruled out that both sets of investor assumptions play a role in investment behavior, but without unambiguous predictions about undetected trading patterns or price dynamics, these models remain highly descriptive in analyzing which types of behavior might cause momentum.

Hong & Stein (1999) come up with a behavioral model that is based on two types of investors with different information sets, but acting rational given their information. The two types of investors are the "news watchers" and "momentum traders". The momentum traders invest in simple trading strategies, conditioning their demand for a stock on the recent price changes of a stock. The news watchers base their value of the firm on the fundamental news that is available to them at a certain point in time. The crucial assumption here is that fundamental news about the firm is only slowly disseminated among the investors, initially leading to underreaction. Arbitrageurs may see this initial price change as an informational trade and their willingness to take advantage of this underreaction they demand this firm's stocks, driving the price further up in subsequent periods. The return in the next period might have gone up because of more good news circulating among the news watchers, but also because of the momentum trader's demand. Momentum traders tend to buy on this recent price increase, leading ultimately to overreaction. In the model of Hong & Stein, momentum traders that buy (sell) just after the arrival of good (bad) news profit at the expense of momentum traders buying when the stock is already overvalued, but on average they take advantage of the underreaction among news watchers. This model predicts that momentum should be more pronounced for firms with low information dissemination. Hong & Stein argue that small stocks and stocks with low analyst coverage are most prone to experience slow diffusion of fundamental news. Empirical observations from Hong et al. (2000) confirm their theoretical predictions to a certain extent.

Barberis & Shleifer (2003) introduce "switchers" and "fundamental traders" as two heterogenous groups of traders to analyze the influence of style investing on the movements in stock prices. Switchers allocate their money among competing styles based on the past relative performance of these styles, leading to some styles that are increasingly popular during a certain period of time. Examples of periods in which an investment style is popular at the expense of others are abundant, recall for example the technology bubble at the end of the 1990s. Fundamental traders make sure that the switchers do not move the asset prices too far away from fundamental values.

The model of Barberis & Shleifer predicts that style momentum strategies are as profitable as asset-level momentum. Their model also implies positive autocorrelations on investment styles on the short run, and negative correlations on the long run, leading to reversals. Parts of this model are empirically validated in Lewellen (2002), who finds similar autocorrelation patterns as predicted by the model of Barberis & Shleifer. Chen (2000) finds that momentum in characteristics is distinct from price momentum. In addition, the strong industry component in momentum strategies might be due to the style component related to industries (e.g. the style and industry "Information technology" are the same).

In conclusion, several behavioral aspects of investors have been modeled and the parameters can be calibrated such that stylized facts from observed stock returns are obtained. Nevertheless, if these models cannot make predictions of unknown return patterns that can subsequently be tested, scepticism about the quality will most likely remain. Recently, Hong et al. (2000) indicate that momentum is higher for firms with low analyst coverage (controlled for firm size), which confirms predictions of the behavior model of Hong & Stein (1999). In addition to these "out of sample" predictions, more convincing evidence can also be provided by research on trading behavior. Recently some papers have investigated assumptions on trading behavior using data of individual investors; see, e.g., Barber & Odean (1999, 2001) or Grinblatt & Keloharju (2001). A fruitful future research area might be to find a behavioral underpinning of the stylized facts about trading volume and price momentum as described in Lee & Swaminathan (2001).[20]

2.7 Transaction costs

The reported excess returns on momentum strategies are easily confused with momentum profits. In order to report attainable profits by investors, transactions costs have to be taken into account. The literature on the momentum effect has neglected to address the issue of transactions cost in detail for a long time. Most papers report the break-even transaction costs and subsequently compare this level with estimates from the transactions costs literature. This leads generally to the conclusion that momentum strategies yield additional return even if transactions costs are taken into account; see, e.g., Jegadeesh & Titman (1993).

Recently, Korajczyk & Sadka (2003) have estimated the transactions costs especially for trading the winner portfolio of the momentum strategies. They distinguish four different approaches to estimate the transactions costs. The first two assume proportional transactions costs. This means that the costs are independent of the trade size. This seems to be unrealistic, as large institutional investors are more prone to impact the stock price than private investors, especially for stocks with small market capitalization. This holds particularly for equally weighted strategies, since momentum strategies often consist of relatively small stocks; see Hong et al. (2000).

The two proportional transactions cost estimates are the effective and quoted spread. The effective spread is the relative difference between the transaction price and midpoint

[20]In addition, Connolly & Stivers (2003) document patterns of trading activity and aggregate stock market returns.

of bid and ask, $ES = \frac{price - \frac{1}{2}(bid+ask)}{\frac{1}{2}(bid+ask)}$. The quoted spread is the ratio between the quoted bid-ask spread and the average of the two, $QS = \frac{ask-bid}{\frac{1}{2}(bid+ask)}$. The two models of Korajczyk & Sadka (2003) that measure price impact are Glosten & Harris (1988) and Breen, Hodrick & Korajczyk (2002). The former model assumes an affine cost function, while the latter assumes a convex cost function of the net trade size.

The gross return of a (5,6) strategy with one-month skip between formation and holding periods is 59 and 33 bp per month for EW and VW strategies, respectively. Note that these excess returns are from the winner versus the market portfolio, instead of the usual winner minus loser strategies. Korajczyk & Sadka argue that short selling requires different transactions costs models and therefore do not consider the loser portfolios.[21] First, we consider the effective spread transactions costs. The net return after these costs are 41 and 22 bp per month for the EW and VW strategies. Second, the quoted spread leads to 35 and 17 bp net returns. The proportional costs reduce the momentum effect considerably, but do not fully explain them.

Using the price impact transactions cost models yields break-even sizes for which the momentum effect can be exploited at the margin. The model of Breen et al. (2002) yields the following results. For equally weighted strategies, the break-even portfolio size is small (below \$ 200 million). According to the transactions cost model of Breen et al., value-weighted strategies can be exploited with portfolios up to a size of \$ 1 billion. The model by Glosten & Harris (1988) yields slightly higher portfolio sizes because of the linearity assumption instead of the convexity in trade size.

Korajczyk & Sadka (2003) also develop a liquidity-based momentum portfolio, which takes into account the transactions costs for the stocks in the momentum portfolio. Their results suggest that a liquidity-based momentum strategy can be exploited with a portfolio of \$ 1.1 billion for NYSE stocks only, and \$ 5 billion for the sample of NYSE, AMEX, and NASDAQ stocks. On the basis of these results, Korajczyk & Sadka conclude that the momentum cannot be explained by transactions costs only.

Lesmond et al. (2003) estimate transactions costs with a limited dependent variable model from Lesmond, Ogden & Trzcinka (1999), using the intuition that stocks with higher trading costs are less frequently traded. Lesmond et al. (2003) compare their results with other trading cost measures such as direct effective spread plus commission, and find that some differences appear for the Jegadeesh & Titman (2001) portfolios, but not for Jegadeesh & Titman (1993) portfolios. In the former, the net excess return is estimated to be 7.12 percent per annum (t-value 2.57) using the direct effective spread plus

[21] Investors already investing in the stock market may implement these momentum strategies by selling stocks already in the portfolio instead of taking short positions. For these investors, transactions costs for both the long and short side of the momentum strategy can be measured using the transactions costs estimators described in this section.

commission, while the Lesmond et al. (1999) estimate gives 4.40 percent (t-value 1.59). For the Jegadeesh & Titman (1993) strategy, the returns are small and insignificant for both transactions costs estimates. The main difference between the two papers of Jegadeesh & Titman is the inclusion of NASDAQ stocks and the exclusion of low priced stocks in the (2001)-paper.

2.8 Summary

In this chapter we survey the momentum literature. We described the economically and statistically significant magnitude of momentum returns that have been reported in the literature, and shed some light on the driving forces behind the momentum effect. The relation of momentum with other firm characteristics, such as for example size, has also been described and linked to both behavioral and risk-based explanations of the momentum effect. Finally, we document some results from an emerging literature on trading costs associated with investing in anomalies. Since no unambiguous explanation for the existence of stock return continuation has been found, research on this topic still has momentum.

Chapter 3

International Industry Momentum

3.1 Introduction

The driving force behind the well-established medium term momentum effect has been the subject of much debate among academics and investment professionals.[1] While one strand of literature aims at the development of theoretical models to explain the existence of this return continuation, another tries to refine the stylized facts about this phenomenon. The new data descriptions may provide evidence about the strengths and weaknesses of the theoretical models, or may help to construct new theories. Evidently, predictions about the persistence of the momentum effect are the driving force behind the research activity on this topic.

The majority of the empirical research is conducted for the US market using the CRSP data tapes. One line of research has focussed of the influence of industry effects on momentum. Moskowitz & Grinblatt (1999) argue that return continuation on the individual stock level is primarily driven by return continuation in industry effects. This type of information is important for finding the driving factors behind the momentum effect. According to their findings, the investor's willingness to be exposed to industry risks is a key determinant for the decision whether to invest in a momentum strategy. They indicate that a momentum strategy in which both the long and short side have the same industry composition does not yield a positive expected return. However, several other papers claim that the industry and individual momentum effects are distinct and can be exploited separately.[2]

In an international context, Richards (1997) and Chan et al. (2000) study the return

[1]See for example Jegadeesh & Titman (1993), Rouwenhorst (1998), and Rouwenhorst (1999b) for evidence on return continuation of stocks between 3–12 months for the US, Europe, and emerging markets, respectively.

[2]See for example Grundy & Martin (2001), Lee & Swaminathan (2001), and Chordia & Shivakumar (2002).

continuation on a country index level. Both papers suggest that a higher expected return can be obtained when conditioning on past six month country performance.[3] The industry composition of these countries differ substantially, so from these results alone it is impossible to infer whether the industry and country momentum effect are related.

The contribution of this paper is to provide evidence on the existence of industry momentum in an international context. More precisely, we study the industry momentum effect in the US, Europe, and Japan. Our results indicate that the presence of industry momentum in the US is not confined to the industry classification used by Moskowitz & Grinblatt (1999). While we also find that European stock markets exhibit medium term industry return continuation, there is virtually no evidence for such phenomenon in Japan.

In addition, we investigate medium term lead-lag effects between the US, Europe, and Japan in order to enhance the attractivity of the momentum strategies under consideration. While there is a literature on the short term (one to five day) lead-lag effects across countries, we are not aware of research on the medium term (six to twelve months). We document that a momentum strategy that ranks US industries and subsequently invests in their European counterparts is more long-lived and has at least as high expected return as the usual momentum strategies. This longer horizon profitability may reduce transaction costs and hence increase portfolio performance.

A possible explanation for these findings is the influence of the macro economy on momentum profits. Recent empirical evidence has indicated that momentum strategies typically perform well during periods in which the macro economic state is favorable, while it does not during recessions; see Chordia & Shivakumar (2002). Since the business cycle has been typically non-synchronous for the three regions under consideration, this may have influenced the performance of industries with a delay.

The motivation of many studies concerning the momentum effect is the question of its persistence. There are two strands of literature dealing with the future possibility to exploit the momentum effect; theoretical and empirical. First, theoretical explanations have been used to explain return continuation. For example, Conrad & Kaul (1998) claim that the dispersion in unconditional expected returns of stocks are the source of the momentum effect. Other types of theoretical models include those of behavioral finance. For example, Daniel et al. (1998) suggest that investors overreact to news on the medium term, initially driving the returns up which is followed by a period of lower returns. On the other hand, Barberis et al. (1998) argue that the momentum effect is due to underreaction of investors to news. They indicate that it takes about six months before news is diffused and valued appropriately by the investing public. The lack of overwhelming empirical

[3]Note that while Chan et al. (2000) find a significant positive momentum effect, the empirical evidence from Richards (1997) is less convincingly positive at the six month horizon.

evidence confirming one type of behavioral explanation keeps the research in this field highly active.

Second, next to these theoretical explanations, researchers have searched for empirical confirmation of return continuation. There seems to be ample empirical evidence supporting persistence of the momentum effect. True out-of-sample evidence over time is available. The initial momentum paper by Jegadeesh & Titman (1993) documented the momentum effect for a sample up to 1989, and Jegadeesh & Titman (2001) report persistence of the momentum effect for the US in the 90-s. The large body of research which claims that for many other markets the momentum effect is also present amplifies the degree of belief in the effect.[4]

The plan of the paper is as follows. In the next section, we briefly describe the data. In Section 3.3, the methodology used for computing the returns on the strategies is explained in detail. Section 3.4 contains the empirical results of our analysis. The first part concentrates on the international presence of industry momentum. The second part deals with the medium term lad-lag effect across regions. In Section 3.5, we correct the returns of international momentum strategies for the three factors of the Fama & French (1993) model. The results of this section can be interpreted as the implications of the international industry momentum effect for a US investor with given exposures to the market, size, and value factor. Finally, Section 3.6 concludes.

3.2 Data

In this analysis we use the Datastream industry indices. The choice for this data source is motivated as follows. In contrast with the US, historical data for Europe and Japan are not readily available, especially when one wants to use coherent industry classifications across regions. The Datastream series have the advantage that it is relatively long compared to other data sources, and widely available among academics and practitioners. Therefore, most results can be replicated by a large audience at relatively low cost.

The industry classification which is used for many US studies is SIC. Aggregation and regrouping of firms in similar fashion to Moskowitz & Grinblatt (1999) does not yield sensible results for European data, since several industries have few or no stocks at all. The results generated by the Datastream industries for the US provide a robustness check on the sensitivity towards the industry classification used in most academic literature for

[4]A recent paper by Lesmond et al. (2003) claims that while the reported findings are not spurious, exploiting the momentum effect is impossible due to the high transactions costs. They argue that a momentum portfolio consists mainly of stocks which are difficult to trade and hence require high transactions costs, exceeding the reported excess rerturns. Unfortunately, we have no data about liquidity or transactions costs of our industry indices, and hence cannot quantify the level of net profit after trading.

the US.

The sample period is January 1973 - April 2000 for all regions.[5] We have return information and market values at an industry level only. An investigation of the performance of individual momentum strategies corrected for the industry momentum effect requires individual stock data, which is not available to us. Papers that aim to disentangle industry and individual momentum effects are Moskowitz & Grinblatt (1999) and Chapter 4 of this thesis. No common European currency existed for a large part of our sample, therefore the European data are converted to a common currency, USD. The US and Japanese data both are in local currency.[6]

The Datastream industries are available on several levels of aggregation. We decided to use the "level four" aggregation. This means that roughly 40 industries are distinguished in each period. The number of industries might be less for a region, since some industries do not exist in a region over the entire sample period. The industry classification does not change over time, and moreover is not backfilled.

Descriptive statistics of the Datastream industries for the three regions are presented in Table 3.1. In general, the average monthly returns on US and European industries are somewhat higher than their Japanese counterparts. For the US and Europe, many industry returns are of similar magnitude. The top performing industry in the US is rather vaguely titled "Other Services" with 1.61 percent per month, while "Investment Companies" is the worst with 0.44 percent. The volatility associated with "Other Services and Businesses" is 10.6 percent per month, the highest of all. The lowest volatility is 4.39 percent for "Electricity". In Europe, the highest average monthly return is 2.33 percent (volatility 9.2) for "Software", and lowest is 0.92 percent (volatility 6.97) for "Household Goods". In Japan three industries have average returns over 2 percent per month,[7] while "Tobacco" has a negative return of -0.17 percent. Industry returns are most volatile in Japan, with five over 10 percent per month.[8] Note that there are three industries for which no funds are listed in Japan over the entire sample period. These industries are "Investment Companies", "Life Assurance", and "Water".

[5] The monthly returns series starts in January 1973. Hence the first observation on the one year historical return is available in December 1973.

[6] The currency is not so important for the investigated strategies, since long-short strategy is only affected by this in the second order $R_{it} \approx R_{it}^{stock} + R_{it}^{forex} \Rightarrow R_{pt}^{excess} \approx R_{it}^{stock} - R_{jt}^{stock}$

[7] "Aerospace and Defence" tops the list with a return of 2.34 percent per month, with associated monthly standard deviation of 11.20 percent.

[8] These five industries are "Aerospace and Defense", "Mining", "Other Services", "Software", and "Telecom Services" with 11.20, 19.85, 13.94, 12.20, and 10.52 percent per month respectively.

Table 3.1: **Description and Summary Statistics of Industries**. Summary statistics of our Datastream "level four" industry classification for the US, Europe, and Japan. The column "mean" contains the average monthly return in percentages, calculated over the sample period the data is available, "std" refers to the standard deviations of the returns and are also in percentages per month. The returns for Europe are obtained from prices converted to USD. Finally, the column labeled "mv" shows the average market value of the industry. Note that these market values are in billions of USD for the US and Europe, and in trillions of JPY for Japan. The entire sample period covers January 1973 - April 2001, but not all industries exist over the full sample.

	US			Europe			Japan		
Industry	mean	std	mv	mean	std	mv	mean	std	mv
Aerospace & Defense	1.40	6.44	48.6	1.45	8.07	10.7	2.34	11.20	0.5
Automobiles	1.03	5.99	67.7	0.92	6.93	49.9	0.98	6.71	14.0
Banks	1.28	5.75	150.9	1.15	5.58	193.8	0.71	7.22	32.4
Beverages	1.26	6.12	73.2	1.11	5.63	24.2	0.71	5.69	2.2
Chemicals	1.09	5.87	82.6	1.11	5.38	62.4	0.72	6.76	8.5
Construction & Materials	1.03	7.07	11.1	1.14	6.26	56.6	0.50	6.36	9.4
Distributors	1.55	9.34	5.7	1.25	6.60	8.4	0.48	6.79	5.6
Diversified Industry	1.04	5.56	35.5	1.15	5.35	53.1	0.85	7.26	0.3
Electricity	1.00	4.39	125.4	1.16	4.90	45.1	0.81	6.87	9.5
Electronic & Electric	1.47	5.94	114.6	1.37	6.00	50.4	0.94	6.51	14.3
Engeneering	1.04	6.25	35.3	1.01	5.65	38.1	0.54	6.35	9.8
Food & Drug Retailers	1.34	5.59	32.8	1.45	6.35	37.0	2.30	8.19	2.9
Food Producers	1.21	4.95	66.6	1.22	5.85	53.0	0.67	5.28	4.0
Forestry & Paper	0.98	7.11	31.4	1.02	6.34	11.9	0.69	6.30	1.5
Gas Distribution	1.28	5.47	21.0	1.46	7.24	13.9	0.85	8.67	2.0

	US			Europe			Japan		
Industry	mean	std	mv	mean	std	mv	mean	std	mv
Househ. Goods & Text.	1.08	6.66	25.5	0.92	6.97	13.9	0.81	6.67	6.5
Healthcare	1.13	5.60	83.1	1.31	6.52	8.2	0.89	8.08	0.4
IT Hardware	1.39	6.57	259.7	2.09	10.17	36.0	1.22	7.94	11.9
Insurance	1.32	5.97	93.2	1.37	5.96	94.8	0.65	7.52	4.1
Investment Companies	0.44	5.67	1.3	1.15	4.95	34.2	–	–	–
Leisure & Hotels	1.42	7.55	48.1	1.18	7.51	15.7	1.39	7.34	1.7
Life Assurance	1.38	6.36	18.9	1.54	6.87	30.6	–	–	–
Media & Photography	1.02	5.59	79.1	1.50	7.47	46.5	1.09	5.98	3.6
Mining	0.96	10.34	3.6	1.38	9.79	8.8	1.73	19.85	0.2
Oil & Gas	1.15	5.46	196.6	1.54	6.55	138.4	0.58	8.30	2.8
Other Serv. & Business	1.61	10.63	22.0	1.09	17.80	0.3	0.93	13.94	0.0
Packaging	1.09	6.28	7.5	1.15	8.30	3.3	1.02	8.93	0.1
Pers. Care & Househ.	1.06	5.43	68.6	1.40	6.29	15.5	0.79	5.64	1.6
Pharmaceuticals	1.38	5.84	175.7	1.59	6.33	63.1	1.16	5.98	6.6
Breweries, Pubs & Rest.	1.26	7.59	16.7	1.36	8.14	12.7	1.07	8.24	0.5
Real Estate	1.18	8.19	14.5	0.96	6.99	22.7	0.64	8.25	3.1
Retailers	1.28	6.90	127.4	1.21	6.91	42.3	0.75	5.91	5.7
Software & Oth. Serv.	1.59	7.62	125.8	2.33	9.15	18.7	2.00	12.2	2.5
Specialty & Oth. Finan.	1.49	7.41	88.7	1.13	7.28	15.6	0.94	8.40	16.0
Steel & Other Metals	1.21	7.79	12.8	0.63	6.78	9.5	0.51	7.93	7.2
Support Services	1.18	6.28	19.8	1.67	7.45	16.1	1.76	8.62	0.7
Telecom Services	1.35	4.51	196.9	1.43	6.04	119.6	1.70	10.52	11.7
Tobacco	1.42	7.11	37.8	1.64	8.26	13.8	-0.17	6.63	1.9
Transport	1.12	6.44	39.5	0.96	5.48	34.1	0.55	5.74	10.7
Water	1.48	6.68	0.6	1.82	7.11	18.4	–	–	–

3.3 Methodology

We consider the set of trading strategies that is proposed in Jegadeesh & Titman (1993). In each month, the industries are ranked in descending order on their (total) return over the last J months. In the next step, ten equally weighted portfolios are formed from all industries under consideration. The top and bottom deciles are called winner and loser portfolio, respectively. A W-L strategy takes a long position in the winner portfolio and a short position of equal size in the loser portfolio. The excess return on this zero investment strategy is defined as the return on the winner minus the return on the loser portfolio. This means that the return on the W-L portfolio is net of a market wide rise or fall.[9] Ranking takes place each month, irrespective of the holding period. We split up the total portfolio in smaller parts. In each month, the strategy consists of a portfolio selected in the current month, as well as K-1 portfolios formed in the previous K-1 months, with K the strategy's holding period. We call a strategy forming deciles on past J month's returns and subsequently holds the portfolio for K months a (J,K) strategy. Thus, each month, the total holding of a (J,K) W-L strategy consists of K portfolios, one W-L portfolio formed at the beginning of this month, and the other K-1 are carried over from the previous months.

This strategy can be rebalanced monthly to maintain equal weights at the beginning of each month. On the other hand, using a buy-and-hold strategy leads to a reduction in transaction costs. Jegadeesh & Titman (1993) report rebalanced results, and note that the returns of a buy-and-hold strategy are slightly higher. For a conservative estimate, the monthly rebalanced portfolios are used throughout this paper when equally weighting the industries.

Since the number of industries varies slightly over time, we decide to use the fixed number of four industries for the winner and loser portfolio for each period in each region. Results on the robustness towards this choice are presented as well.

Lo & MacKinlay (1990a) document that the existence of serial correlation in portfolio returns might be due to lead-lag effects. These lead-lag effects are related to firm size, while the smaller firms tend to lag the larger ones. On the daily horizon this might be due to thin trading in small stocks. Other market micro structure effects like the bid-ask bounce may also play a role in the observed returns on the daily horizon. On longer horizons the explanation of thin trading is less convincing, but it is often assumed that small firms react slowly to common risk factors. This lead-lag effect is strongest on short horizons, and might account for a substantial part of the positive expected excess return. Since it is unlikely that the lead-lag effect can be exploited by trading, the raw results may be illusionary. If these lead-lag effects are driving our results, they do this close to the

[9] The return is only truly net of a market effect under the assumption that both the long and the short side of the investment strategy are equally sensitive to the market as a whole.

beginning of the investment period. Therefore, it is important to examine the influence of price reactions closely after the formation period. We decide to correct for this potential lead-lag effect by skipping one month between formation and holding period.

There is a widespread belief that the US is the leading economy world-wide, which means that news is generated in the US and spreads slowly among the investors around the world. Most research is focused on the daily influence of return patterns on the major global stock exchanges. In this paper, we try to exploit longer-run dependencies across regions. In the usual momentum strategies as presented in this paper, industries are ranked on their past performance and subsequently the top (bottom) four are long (short) in the momentum portfolio. We also investigate strategies which rank industries from one region in the world, e.g. US, and subsequently invest in the same industries in other regions in the world, e.g. Europe. For this exercise, it is important that we have a consistent industry classification across regions, which is the case for our data. In order to reduce the influence of time-lags[10] and lead-lag effects we again skip one-month between portfolio formation and investment.

3.4 Empirical results

This section is divided in two parts. In the first part, we discuss the results obtained for the industry momentum strategies for our data set. Our results are compared with other empirical literature in this field. The second part is devoted to the investigation of cross-border industry momentum effects. We show results of strategies when formation industries are from different regions than the industries invested in.

3.4.1 Industry momentum effect

We employ the Jegadeesh & Titman (1993) method as described above and use the fixed number of four industries for the winner and loser portfolios. In Table 3.2 the results are presented from the zero-investment momentum strategies with different formation and holding periods up to one year.[11] A closer look on the table shows that many patters observed in the individual stock momentum literature seem to hold for momentum on an industry level too. For the US, the momentum effect with a formation period of

[10]The US closing prices will generally contain information from one extra trading day relative to the Japanese market, because of the different time zones they are in. New information emerging in times that the US market is open and the European or Japanese market are closed might affect prices of foreign stocks the next day.

[11]Results without one month skip are presented in the tables, but not extensively discussed in the main text. The choice of four industries in the winner and four in the loser portfolio is fairly robust, we also present returns for the top and bottom eight industries in Table 3.3. Unreported results indicate that our results are not driven by the January effect.

Table 3.2: **Industry momentum for US, Europe, and Japan, 1974–2000, one-month skip**. In this table we present the expected excess returns of a long postition in the top four industries and a short position in the bottom four industries per region. Within the industries stocks are value weighted, but equally weighting is performed across industries in the strategy. In order to reduce the potential influence of market micro structure effects or lead-lag relationships we skip one month between formation and investment. The t-values are presented in parenthesis. In Panel A, B, and C the results are presented for the US, Europe, and Japan, respectively.

Panel A		Holding				
US		1	3	6	9	12
	1	-0.29 (-1.02)	-0.23 (-1.26)	-0.15 (-1.10)	0.06 (0.51)	0.17 (1.58)
	3	-0.39 (-1.29)	-0.28 (-1.13)	0.01 (0.04)	0.26 (1.57)	0.19 (1.23)
Formation	6	0.03 (0.01)	0.09 (0.33)	0.44 (1.79)	0.49 (2.14)	0.30 (1.40)
	9	0.34 (1.03)	0.51 (1.72)	0.55 (1.95)	0.41 (1.59)	0.22 (0.90)
	12	0.31 (0.95)	0.32 (1.01)	0.28 (0.98)	0.20 (0.72)	0.19 (0.74)

Panel B		Holding				
EU		1	3	6	9	12
	1	0.20 (0.58)	0.31 (1.50)	0.06 (0.36)	0.15 (1.06)	0.16 (1.23)
	3	0.69 (2.04)	0.56 (2.01)	0.50 (2.13)	0.53 (2.44)	0.36 (1.87)
Formation	6	0.52 (1.52)	0.60 (1.98)	0.63 (2.28)	0.50 (1.91)	0.29 (1.20)
	9	0.61 (1.73)	0.70 (2.21)	0.60 (1.96)	0.44 (1.55)	0.20 (0.71)
	12	0.69 (1.93)	0.55 (1.67)	0.46 (1.51)	0.26 (0.89)	0.10 (0.39)

Panel C		Holding				
JP		1	3	6	9	12
	1	-0.82 (-1.87)	-0.06 (-0.19)	0.05 (0.20)	0.11 (0.56)	0.17 (1.04)
	3	0.02 (0.04)	0.16 (0.38)	0.15 (0.43)	0.21 (0.72)	0.25 (1.05)
Formation	6	0.18 (0.38)	0.27 (0.61)	0.28 (0.70)	0.33 (1.02)	0.04 (0.11)
	9	0.38 (0.79)	0.49 (1.06)	0.52 (1.32)	0.24 (0.63)	0.05 (0.14)
	12	0.46 (1.04)	0.38 (0.89)	0.11 (0.26)	-0.05 (-0.11)	-0.15 (-0.43)

three months does not yield an expected return significantly different from zero for all investment horizons. For the medium term strategy with a formation and holding period of six months the excess return of 0.44 percent per month is significantly positive at a 10 percent confidence level. For strategies with nine month formation period the momentum effect is present too, while the 0.19 percent per month for the one year strategy is not significant. So, these results indicate that industry momentum is a medium term effect only. The results without skipping a month are presented in Table 3.4, we note that not surprisingly the largest difference is obtained when the formation and holding period are short. For the one month formation and holding period the expected monthly excess returns drops from 0.67 to -0.29 percent.

Moskowitz & Grinblatt (1999) report a declining expected return for equally weighted top three industry strategies including a one month skip. In their paper, the one, six, and twelve month formation and holding period the return is 0.01, 0.40, and 0.23 percent respectively, when one month is skipped. This is close to the -0.29, 0.44, and 0.19 we find for our sample. In their paper, the expected return also drops significantly on short horizons when one month is skipped between formation and investment period. Without skipping they find a highly significant 1.05 percent monthly excess return, which is somewhat higher than the 0.67 we find. Nevertheless, both results indicate that without skipping a month the one-month strategy yields a highly significant excess return, while with skipping the first month this vanishes. Since our results are so similar to Moskowitz & Grinblatt (1999), we conclude that the industry momentum effect is fairly robust for the choice of industry classification.

Since we do not have the data on an individual stock level available, we cannot verify whether the industry momentum effect subsumes the individual momentum effect. Intuitively, the industry effect seems to capture only part of the full momentum effect, since Jegadeesh & Titman (2001) report excess returns of about one percent per month for a six month strategy on an individual stock level. At least at first glance, our results seems to indicate that on the medium term roughly half of the momentum effect is explained by the industry momentum effect. However, the equal weighting typically undertaken in individual stock momentum studies versus the value weighting of our industry portfolios might be responsible for this difference in expected returns. Several studies, Hong et al. (2000) amongst other, indicated that the momentum effect is more pronounced for small firms than for large firms. Unfortunately, without the individual stock data we cannot investigate this issue any further. The simultaneous effect of countries and industries in Europe is further investigated in Chapter 4 of this thesis. Their results indicate that an individual momentum effect in Europe exists in the 90-s after controlling for both industry and country momentum.

For the European market, the returns for the momentum strategies are reported in

Table 3.3: **Industry momentum for US, Europe, and Japan, 1974–2000, one-month skip with 8 instead of 4 industries**. In this table we present the expected excess returns of a long postition in the top eight industries and a short position in the bottom eight industries per region. Within the industries stocks are value weighted, but equally weighting is performed across industries in the strategy. In order to reduce the potential influence of market micro structure effects or lead-lag relationships we skip one month between formation and investment. The t-values are presented in parenthesis. In Panel A, B, and C the results are presented for the US, Europe, and Japan, respectively.

Panel A		Holding				
US		1	3	6	9	12
	1	-0.24 (-1.13)	-0.14 (-1.02)	-0.08 (-0.81)	0.08 (0.94)	0.13 (1.70)
	3	-0.34 (-1.61)	-0.19 (-1.05)	0.03 (0.20)	0.24 (1.84)	0.19 (1.50)
Formation	6	-0.16 (-0.69)	0.07 (0.34)	0.35 (1.86)	0.40 (2.30)	0.25 (1.57)
	9	0.20 (0.81)	0.34 (1.47)	0.47 (2.19)	0.38 (1.93)	0.22 (1.19)
	12	0.43 (1.74)	0.34 (1.44)	0.34 (1.54)	0.26 (1.21)	0.20 (1.00)

Panel B		Holding				
EU		1	3	6	9	12
	1	0.10 (0.44)	0.18 (1.27)	0.09 (0.83)	0.12 (1.24)	0.13 (1.57)
	3	0.54 (2.34)	0.36 (1.86)	0.30 (1.91)	0.33 (2.18)	0.25 (1.81)
Formation	6	0.43 (1.88)	0.39 (1.83)	0.47 (2.38)	0.39 (2.12)	0.23 (1.36)
	9	0.51 (2.16)	0.62 (2.71)	0.52 (2.37)	0.38 (1.86)	0.20 (0.96)
	12	0.71 (2.75)	0.56 (2.27)	0.38 (1.66)	0.23 (1.07)	0.13 (0.70)

Panel C		Holding				
JP		1	3	6	9	12
	1	-0.35 (-1.17)	-0.01 (-0.05)	0.05 (0.34)	0.08 (0.64)	0.10 (0.91)
	3	0.08 (0.23)	0.21 (0.74)	0.25 (1.04)	0.27 (1.35)	0.25 (1.42)
Formation	6	0.43 (1.31)	0.35 (1.16)	0.37 (1.36)	0.38 (1.60)	0.20 (0.89)
	9	0.20 (0.59)	0.31 (0.98)	0.39 (1.38)	0.21 (0.79)	0.08 (0.33)
	12	0.45 (1.36)	0.40 (1.29)	0.24 (0.84)	0.11 (0.41)	0.03 (0.13)

Table 3.4: **Industry momentum for US, Europe, and Japan, 1974–2000, no one-month skip**. In this table we present the expected excess returns of a long postition in the top four industries and a short position in the bottom four industries per region. Within the industries stocks are value weighted, but equally weighting is performed across industries in the strategy. The t-values are presented in parenthesis. In Panel A, B, and C the results are presented for the US, Europe, and Japan, respectively.

Panel A		Holding				
US		1	3	6	9	12
	1	0.67 (2.41)	0.05 (0.32)	-0.03 (-0.22)	0.12 (1.02)	0.20 (1.96)
	3	0.13 (0.44)	-0.19 (-0.75)	-0.07 (-0.35)	0.20 (1.16)	0.26 (1.63)
Formation	6	-0.16 (-0.51)	-0.05 (-0.17)	0.20 (0.80)	0.47 (2.04)	0.35 (1.61)
	9	0.39 (1.18)	0.39 (1.29)	0.53 (1.89)	0.48 (1.82)	0.29 (1.15)
	12	0.53 (1.64)	0.38 (1.24)	0.35 (1.22)	0.28 (1.03)	0.17 (0.67)

Panel B		Holding				
EU		1	3	6	9	12
	1	1.06 (3.23)	0.61 (2.72)	0.25 (1.59)	0.25 (1.81)	0.25 (1.87)
	3	0.96 (2.82)	0.78 (2.77)	0.56 (2.34)	0.57 (2.65)	0.45 (2.25)
Formation	6	0.71 (2.10)	0.64 (2.07)	0.64 (2.30)	0.57 (2.18)	0.37 (1.53)
	9	0.80 (2.30)	0.77 (2.41)	0.64 (2.08)	0.50 (1.74)	0.31 (1.13)
	12	0.77 (2.41)	0.74 (2.18)	0.57 (1.80)	0.39 (1.30)	0.15 (0.54)

Panel C		Holding				
JP		1	3	6	9	12
	1	0.67 (1.64)	0.12 (0.46)	0.07 (0.34)	0.15 (0.79)	0.21 (1.22)
	3	0.24 (0.53)	0.18 (0.46)	0.16 (0.48)	0.22 (0.79)	0.27 (1.10)
Formation	6	0.46 (0.96)	0.33 (0.71)	0.27 (0.66)	0.33 (0.97)	0.18 (0.58)
	9	0.38 (0.78)	0.36 (0.78)	0.51 (1.25)	0.37 (0.94)	0.14 (0.38)
	12	0.42 (0.83)	0.39 (0.89)	0.24 (0.57)	0.04 (0.11)	-0.07 (-0.20)

Panel B of Table 3.2. Generally, we can conclude from this table that the industry momentum effect is more pronounced in Europe than the US. For example, the strategy with a six month formation and holding period returns 0.63 percent per month for Europe versus 0.44 percent for the US. These returns are both economically and statistically significant at the 10 percent level (t-values 2.27 and 1.79 respectively). The overall pattern for Europe is also the same as for the US. Comparing the magnitude of these excess returns to the individual stock momentum strategy for the European market reported by Rouwenhorst (1998) suggests again that about half the momentum effect is captured by the industry momentum effect. Also for European markets the momentum effect seems to be most pronounced for the smaller stocks, so our value weighted industry indices might be difficult to compare with the equally weighted portfolios used by Rouwenhorst (1998).

The performance of the Japanese industry momentum strategies are displayed in Panel C of Table 3.2. These results are different from Europe and the US. There is no industry momentum strategy with combinations between three and twelve months that renders significant positive excess returns. For example, the six month strategy returns 0.28 percent per month with a t-value of 0.70. The absence of the industry momentum effect should not come as a big surprise since studies on individual stocks indicate no individual momentum profits on the medium term for Japan; see e.g. Hameed & Yuanto (2002). Though in principle it is possible to find an industry momentum effect without an individual stock momentum effect, this appears not to be the case in Japan. If this were to be the case, then individual stock effects should work exactly opposite to the industry effects.[12]

The results presented above are based on strategies which equally weight the returns of the top and bottom four industries. This means that the smallest industry is equally important as the largest industry. To reduce the importance of the small industries, we use a subsample of the 20 industries with largest market value at each point in time and perform a momentum strategy on this subsample. Again, we are long in the top four industries and short in the bottom four industries. In Table 3.5 the results of these strategies are presented. The statistical evidence for international industry momentum has reduced for all regions, but the economic magnitude of the excess returns is still substantial, between 0.32 and 0.55 percent per month for the (6,6) strategy. These results indicate that the small industries are not distorting the momentum analysis presented before, and that there is industry momentum when only the largest half of the industries is considered. Thus, we conclude that industry momentum is a global phenomenon.

[12] Consider the following example. There are six stocks of equal size, A, B and C belong to industry I and D, E and F belong to industry II. The return of these four stocks is alternatingly $(4, 1, 3, 4, 1, 2)$ and $(1, 4, 3, 1, 4, 2)$ for a large number of times. The individual momentum strategy (buy top two stocks, sell bottom two) yields always an excess return of -3, while the industry momentum strategy (buy winner industry, sell loser industry) yields always $\frac{1}{3}$. This is an example which shows that industry momentum might exist while at the individual stock level return reversals exist.

Table 3.5: **Industry momentum for US, Europe, and Japan, 1974–2000, one-month skip with largest 20 industries.** In this table we present the expected excess returns of a long postition in the top four industries and a short position in the bottom four industries per region, when only the 20 largest at each point in time are considered. Within the industries stocks are value weighted, and equal weighting is performed across industries in the strategy. In order to reduce the potential influence of market micro structure effects or lead-lag relationships we skip one month between formation and investment. The t-values are presented in parenthesis. In Panel A, B, and C the results are presented for the US, Europe, and Japan, respectively.

Panel A		Holding				
US		1	3	6	9	12
	1	-0.42 (-1.46)	-0.36 (-2.13)	-0.21 (-1.66)	0.01 (0.11)	0.02 (0.26)
	3	-0.55 (-1.97)	-0.40 (-1.73)	-0.05 (-0.27)	0.19 (1.27)	0.10 (0.65)
Formation	6	-0.25 (-0.83)	-0.02 (-0.07)	0.33 (1.43)	0.32 (1.53)	0.05 (0.26)
	9	0.14 (0.47)	0.34 (1.22)	0.38 (1.44)	0.15 (0.60)	-0.05 (-0.20)
	12	0.28 (0.93)	0.12 (0.42)	0.11 (0.39)	-0.02 (-0.09)	-0.11 (-0.47)

Panel B		Holding				
EU		1	3	6	9	12
	1	0.08 (0.25)	0.22 (1.06)	0.04 (0.37)	0.11 (0.76)	0.11 (0.83)
	3	0.58 (1.79)	0.44 (1.64)	0.32 (1.40)	0.36 (1.66)	0.28 (1.41)
Formation	6	0.51 (1.56)	0.50 (1.67)	0.55 (1.94)	0.44 (1.63)	0.28 (1.14)
	9	0.44 (1.30)	0.60 (1.87)	0.51 (1.66)	0.37 (1.28)	0.17 (0.62)
	12	0.64 (1.79)	0.56 (1.64)	0.40 (1.25)	0.22 (0.74)	0.08 (0.31)

Panel C		Holding				
JP		1	3	6	9	12
	1	-0.50 (-1.19)	0.02 (0.07)	0.06 (0.28)	0.05 (0.28)	0.08 (0.51)
	3	0.25 (0.58)	0.26 (0.71)	0.15 (0.47)	0.17 (0.65)	0.25 (1.18)
Formation	6	0.57 (1.34)	0.37 (0.92)	0.34 (0.89)	0.42 (1.40)	0.21 (0.74)
	9	0.35 (0.79)	0.39 (0.90)	0.46 (1.29)	0.21 (0.62)	0.02 (0.05)
	12	0.84 (2.14)	0.59 (1.55)	0.27 (0.72)	0.05 (0.15)	-0.06 (-0.18)

3.4.2 International industry lead-lag effects

In this section we address the question whether lead-lag effects are responsible for return continuation. Lead-lag effects might exist between large and small stocks, but also between international markets. It is generally believed that the US business cycle does not move together with the business cycles of Europe or Japan.[13] This notion might be exploitable in a momentum context. Industries that are performing well in the US today, might be the industries that outperform in Europe tomorrow. Therefore, we evaluate another momentum-like strategy. Industries are selected on the performance of the leading market, while investment takes place in the same industries of the lagging markets. The investigated strategies are again similar to those of Jegadeesh & Titman (1993).

It is often argued that the US is the leading world market; see e.g. Copeland & Copeland (1998). They claim that the US is leading one day over the Pacific and Europe, both on a country and an industry level by investigating autocorrelation in the return series. Daily lags two up to four are not significantly different from zero, and longer horizons are not considered. They conclude: "*We did not explicitly test another (possibly more profitable) trading strategy, namely, exploiting global industry momentum across borders.*" This subsection of our paper is aimed at doing exactly that, albeit with longer formation and holding periods.

In Table 3.6, the formation takes place on the US industries, while investment takes place on their European counterparts. Interestingly, this table suggests that investing on US industries instead of European industries results in about the same expected return, but a lower volatility on the zero-investment portfolio. The momentum effect is statistically significant at the 3–12 month horizon, which is not the case when European industries themselves are used for ranking. So, the strategies based on US ranking seems to be more long-lived, and implementing this strategy could reduce transaction costs and hence increase net performance.

The results for Japan are also noteworthy. The strategy with formation and holding period of six months has an expected return of 0.41 percent per month, which has a p-value just above five percent (t-value 1.94). The strength of these strategies seem to decrease when moving away from this particular combination of formation and holding period. We therefore do not conclude that there is a significant lead-lag effect between the US and Japan. Nevertheless, it appears to generate a higher excess return to implement an industry momentum strategy in Japan based on past US industry returns than on Japanese industries.

[13] Interesting papers relating momentum strategies to the state of the macro economy are for example Chordia & Shivakumar (2002), Wu (2001), Cooper, Gutierrez & Hameed (2001) and Bacmann, Dubois & Isakov (2001).

Table 3.6: **Cross region industry momentum with US leading, 1974–2000, one month skip**. In this table we present the excess returns of a strategy that is long (short) in the four industries for which their US counterparts obtained highest (lowest) recent past returns. In order to reduce the potential influence of market micro structure effects and lead-lag relation we skip one month between formation and investment. T-values are presented in parenthesis. In Panel A and B the results for investments in Europe and Japan are displayed, respectively.

Panel A		Holding				
US -> EU		1	3	6	9	12
	1	0.69 (2.76)	0.39 (2.09)	0.18 (1.52)	0.26 (2.62)	0.28 (3.11)
	3	0.46 (1.66)	-0.01 (-0.05)	0.09 (0.60)	0.23 (1.67)	0.23 (1.95)
Formation	6	0.39 (1.46)	0.28 (1.19)	0.42 (2.11)	0.49 (2.75)	0.42 (2.52)
	9	0.64 (2.27)	0.51 (2.01)	0.63 (2.85)	0.57 (2.76)	0.49 (2.47)
	12	0.79 (2.80)	0.65 (2.72)	0.60 (2.69)	0.54 (2.52)	0.51 (2.68)

Panel B		Holding				
US -> JP		1	3	6	9	12
	1	0.22 (0.63)	0.22 (1.14)	0.13 (1.04)	0.11 (1.10)	0.12 (1.30)
	3	0.22 (0.79)	0.07 (0.24)	0.03 (0.20)	0.07 (0.49)	0.03 (0.20)
Formation	6	0.56 (1.91)	0.37 (1.43)	0.41 (1.94)	0.35 (1.83)	0.18 (1.00)
	9	0.49 (1.66)	0.37 (1.49)	0.23 (0.96)	0.17 (0.72)	0.14 (0.59)
	12	0.38 (1.39)	0.25 (0.98)	0.10 (0.41)	0.10 (0.38)	0.09 (0.36)

Table 3.7: **Cross region industry momentum with Europe leading, 1974–2000, one month skip**. In this table we present the excess returns of a strategy that is long (short) in the four industries for which their European counterparts obtained highest (lowest) recent past returns. In order to reduce the potential influence of market micro structure effects and lead-lag relation we skip one month between formation and investment. T-values are presented in parenthesis. In Panel A and B the results for investments in the US and Japan are displayed, respectively.

Panel A		Holding				
EU -> US		1	3	6	9	12
	1	0.17 (0.74)	0.02 (0.17)	0.09 (0.89)	0.13 (1.46)	0.13 (1.59)
	3	0.05 (0.19)	0.09 (0.45)	0.12 (0.74)	0.28 (1.90)	0.15 (1.06)
Formation	6	0.19 (0.81)	0.11 (0.49)	0.20 (1.05)	0.16 (0.86)	0.03 (0.20)
	9	0.38 (1.60)	0.41 (1.85)	0.28 (1.31)	0.20 (0.98)	0.05 (0.25)
	12	0.21 (0.88)	0.05 (0.21)	0.06 (0.28)	-0.02 (-0.10)	-0.05 (-0.25)

Panel B		Holding				
EU -> JP		1	3	6	9	12
	1	0.35 (1.23)	0.03 (0.18)	0.03 (0.25)	0.17 (1.23)	0.19 (1.90)
	3	0.33 (1.19)	0.09 (0.38)	0.15 (0.63)	0.31 (1.43)	0.29 (1.61)
Formation	6	0.26 (0.96)	0.14 (0.49)	0.32 (1.11)	0.42 (1.56)	0.34 (1.51)
	9	0.37 (1.04)	0.41 (1.27)	0.42 (1.32)	0.39 (1.42)	0.35 (1.46)
	12	0.84 (2.32)	0.58 (1.71)	0.50 (1.67)	0.47 (1.84)	0.41 (1.79)

Table 3.8: **Cross region industry momentum with Japan leading, 1974–2000, one month skip**. In this table we present the excess returns of a strategy that is long (short) in the four industries for which their Japanese counterparts obtained highest (lowest) recent past returns. In order to reduce the potential influence of market micro structure effects and lead-lag relation we skip one month between formation and investment. T-values are presented in parenthesis. In Panel A and B the results for investments in the US and Europe are displayed, respectively.

Panel A		Holding				
JP -> US		1	3	6	9	12
	1	-0.07 (-0.38)	-0.10 (-0.80)	-0.06 (-0.69)	0.02 (0.29)	0.03 (0.48)
	3	-0.17 (-0.80)	-0.20 (-1.23)	0.01 (0.06)	0.05 (0.41)	-0.00 (-0.01)
Formation	6	-0.33 (-1.52)	-0.08 (-0.45)	0.09 (0.56)	0.08 (0.53)	0.04 (0.29)
	9	0.04 (0.21)	0.04 (0.19)	0.05 (0.26)	0.05 (0.32)	0.05 (0.30)
	12	-0.15 (-0.68)	-0.11 (-0.53)	-0.03 (-0.17)	0.02 (0.11)	0.05 (0.25)

0

Panel B		Holding				
JP -> EU		1	3	6	9	12
	1	0.52 (2.47)	0.16 (1.27)	0.16 (1.73)	0.14 (1.71)	0.13 (1.61)
	3	0.12 (0.54)	0.03 (0.16)	0.16 (1.16)	0.14 (1.19)	0.13 (1.22)
Formation	6	0.26 (1.17)	0.15 (0.82)	0.21 (1.33)	0.24 (1.62)	0.21 (1.58)
	9	0.19 (0.86)	0.21 (1.03)	0.27 (1.48)	0.27 (1.59)	0.28 (1.78)
	12	0.42 (1.77)	0.32 (1.60)	0.30 (1.60)	0.32 (1.71)	0.26 (1.48)

In order to investigate which region influences which, we also repeat the analysis with the formation based on European and Japanese industries. The results for Europe are displayed in Table 3.7. Our results suggest that the lead-lag influence from Europe to the US does not follow a nice pattern, though most expected returns are positive. It is clear, however, that ranking on European industries does not increase the expected return on US momentum strategies. In Panel B, the return on the Japanese industry momentum strategy ranked on the basis of European industries are presented. The results from this panel indicate that when a one-year formation period is considered, expected returns on all holding periods are significant on the 10 percent level. The expected excess return for such strategy with a holding period of one year is 0.41 percent per month. Our results suggest that there is a one year lead-lag relationship between industry returns in Europe and Japan. This means that the industries that performed best (worst) in Europe over the past year, tend to be best (worst) in Japan over the next year. Differences in the business cycle could be causing this lead-lag relationship.

The results with ranking on the Japanese industries are presented in Table 3.8. Apparently, selecting on Japanese industries and investing in their counterparts in the US and Europe does not yield a positive expected return. The exception is the strategy with

Table 3.9: **Cross region industry momentum with US leading, 1974–2000, no skip**. In this table we present the excess returns of a strategy that is long (short) in the four industries for which their US counterparts obtained highest (lowest) recent past returns. T-values are presented in parenthesis. In Panel A and B the results for investments in Europe and Japan are displayed, respectively.

Panel A		Holding				
US -> EU		1	3	6	9	12
	1	0.93 (3.96)	0.69 (4.46)	0.32 (2.55)	0.32 (3.55)	0.31 (3.45)
	3	1.03 (4.01)	0.46 (2.11)	0.19 (1.13)	0.32 (2.28)	0.31 (2.53)
Formation	6	0.91 (3.24)	0.48 (1.99)	0.45 (2.20)	0.51 (2.84)	0.47 (2.79)
	9	0.87 (2.91)	0.62 (2.31)	0.63 (2.75)	0.62 (2.97)	0.56 (2.80)
	12	0.98 (3.29)	0.75 (2.92)	0.67 (2.91)	0.61 (2.81)	0.53 (2.60)

Panel B		Holding				
US -> JP		1	3	6	9	12
	1	0.90 (3.48)	0.55 (3.13)	0.31 (2.14)	0.19 (1.94)	0.19 (2.20)
	3	0.64 (2.35)	0.22 (0.91)	0.12 (0.64)	0.14 (1.00)	0.11 (0.82)
Formation	6	1.01 (2.56)	0.62 (2.01)	0.51 (2.14)	0.49 (2.52)	0.31 (1.70)
	9	0.76 (2.60)	0.55 (2.15)	0.39 (1.70)	0.26 (1.15)	0.20 (0.91)
	12	0.60 (2.07)	0.39 (1.50)	0.23 (0.95)	0.16 (0.68)	0.14 (0.59)

one-month formation and one-month holding period for Europe, which shows a significant 0.52 percent per month expected return. However, such short term trading strategy would incur high transactions costs due to frequent trading. This will probably eliminate all potential profits from this strategy.

3.5 Portfolio implications for industry momentum strategies

In the previous section we established the existence of the industry momentum effect for the US and Europe, but not for Japan. These high excess returns could be just a compensation for bearing more risk. One way to look at riskiness is to determine the loadings on the Fama & French (1993) three factor model, which corrects for riskiness relative to the market, the size, and value factor unconditionally. We determine whether the strategies with positive excess returns can be explained by higher loadings on these risk factors. If this turns out to be the case, an industry momentum strategy can be replicated by the factor mimicking portfolios and the risk free asset. The mimicking portfolio will have the same expected returns as the industry momentum effect, but a lower volatility.

The three factor model by Fama & French (1993) states that the expected return

Table 3.10: **Cross region industry momentum with Europe leading, 1974–2000, no skip**. In this table we present the excess returns of a strategy that is long (short) in the four industries for which their European counterparts obtained highest (lowest) recent past returns. T-values are presented in parenthesis. In Panel A and B the results for investments in the US and Japan are displayed, respectively.

Panel A		Holding				
EU -> US		1	3	6	9	12
	1	0.49 (2.15)	0.17 (1.21)	0.11 (1.03)	0.13 (1.41)	0.20 (2.42)
	3	0.33 (1.33)	0.18 (0.90)	0.13 (0.82)	0.25 (1.71)	0.23 (1.68)
Formation	6	0.02 (0.10)	0.09 (0.45)	0.13 (0.68)	0.17 (0.93)	0.07 (0.44)
	9	0.32 (1.27)	0.36 (1.60)	0.31 (1.47)	0.24 (1.18)	0.11 (0.61)
	12	0.44 (1.86)	0.19 (0.85)	0.13 (0.60)	0.05 (0.25)	-0.02 (-0.12)

Panel B		Holding				
EU -> JP		1	3	6	9	12
	1	0.25 (0.89)	0.22 (1.22)	0.14 (0.94)	0.13 (0.98)	0.21 (1.80)
	3	0.60 (2.12)	0.35 (1.54)	0.20 (0.95)	0.29 (1.31)	0.35 (1.99)
Formation	6	0.69 (1.82)	0.34 (1.18)	0.32 (1.11)	0.46 (1.71)	0.38 (1.59)
	9	0.62 (1.68)	0.46 (1.39)	0.49 (1.52)	0.42 (1.41)	0.38 (1.50)
	12	0.77 (2.13)	0.69 (2.00)	0.57 (1.76)	0.51 (1.89)	0.47 (1.97)

relative to the risk free rate of any asset can be written like

$$E\{R^e_{i,t}\} = \beta_i(E\{R_{m,t}\} - R_f) + s_i E\{R_{smb,t}\} + h_i E\{R_{hml,t}\}$$

with $R^e_{i,t}$ the (excess) return of asset i in period t, with subscript f for risk free, m for the market, *smb* for the small minus large stocks, and *hml* for the high value minus low value stocks portfolio. A regression model can be used to determine the exposures to the risk factors for possibly interesting portfolios. The regression equation is

$$R^e_{i,t} = \alpha_i + \beta_i\left(R_{m,t} - R_f\right) + s_i R_{smb,t} + h_i R_{hml,t} + \varepsilon_{i,t}$$

This model can be estimated by ordinary least squares (OLS), and standard errors can be corrected for possible heteroskedasticity and autocorrelation by using the covariance matrix by Newey & West (1987). For a portfolio to be attractive relative to these risk factors, the constant term (α_i) should be positive. That way the new asset has a higher expected return than an existing portfolio with fixed weights for the risk factors.[14]

The risk corrected expected returns are displayed in Table 3.12. The results indicate that for an investor who already owns a combination of the three Fama-French portfo-

[14]The data for the factor mimicking portfolios are obtained from the website of Kenneth French.

Table 3.11: **Cross region industry momentum with Japan leading, 1974–2000, no skip**. In this table we present the excess returns of a strategy that is long (short) in the four industries for which their Japanese counterparts obtained highest (lowest) recent past returns. T-values are presented in parenthesis. In Panel A and B the results for investments in the US and Europe are displayed, respectively.

Panel A		Holding				
JP -> US		1	3	6	9	12
	1	-0.02 (-0.11)	0.02 (0.21)	-0.10 (-1.00)	-0.01 (-0.12)	0.02 (0.36)
	3	0.04 (0.22)	-0.12 (-0.71)	-0.03 (-0.27)	0.04 (0.33)	0.02 (0.22)
Formation	6	-0.15 (-0.68)	-0.16 (-0.88)	0.01 (0.07)	0.05 (0.37)	0.05 (0.34)
	9	0.15 (0.69)	0.11 (0.59)	0.05 (0.28)	0.07 (0.42)	0.05 (0.29)
	12	0.13 (0.60)	-0.03 (-0.14)	-0.02 (-0.10)	0.01 (0.07)	0.02 (0.13)

Panel B		Holding				
JP -> EU		1	3	6	9	12
	1	0.38 (1.73)	0.32 (2.69)	0.18 (1.90)	0.17 (2.14)	0.15 (1.91)
	3	0.22 (1.03)	0.12 (0.73)	0.14 (1.03)	0.13 (1.07)	0.15 (1.36)
Formation	6	0.04 (0.16)	0.11 (0.56)	0.20 (1.24)	0.23 (1.52)	0.19 (1.42)
	9	0.10 (0.45)	0.13 (0.66)	0.22 (1.22)	0.25 (1.46)	0.26 (1.62)
	12	0.10 (0.41)	0.29 (1.34)	0.28 (1.48)	0.29 (1.60)	0.29 (1.64)

Table 3.12: **Expected returns and exposures on (6,6) strategies relative to Fama-French risk factors**. In this table we present the estimation results of five industry momentum portfolios relative to the three-factor asset pricing model by Fama and French. The regression equation is $R_t^{MOM} = \alpha + \beta \cdot RMRF_t + s \cdot SMB_t + h \cdot HML_t + \varepsilon_t$ where $RMRF$ is the excess return on the market, SMB the excess return of a portfolio of small stocks over a portfolio of large stocks, and HML the excess return of a portfolio of stocks with high book-to-market ratios over a portfolio of stocks with a low book-to-market ratio. The sample period is 1974:2 to 2000:4. All strategies presented have a formation and holding period of six months. The strategy USA(6) -> EUR(6) refers to a formation on US industries with formation period of 6 months, and investment in the European industries with holding period of 6 months. The standard errors to calculate the t-values are heteroskedasticity and autocorrelation consistent.

Formation	Holding	a	b	s	h
EUR(6) ->	EUR(6)	0.83 (2.89)	-0.13 (-1.33)	-0.12 (-0.98)	-0.29 (-2.04)
USA(6) ->	USA(6)	0.42 (1.79)	0.07 (0.62)	0.14 (1.26)	-0.17 (-1.07)
JAP(6) ->	JAP(6)	0.36 (0.87)	-0.10 (-1.14)	0.11 (0.90)	-0.09 (-0.50)
USA(6) ->	EUR(6)	0.47 (1.94)	-0.02 (-0.33)	0.10 (0.96)	-0.20 (-1.67)
USA(6) ->	JAP(6)	0.46 (1.97)	-0.03 (-0.35)	0.09 (1.29)	-0.16 (-1.81)
EUR (6) ->	JAP(6)	0.35 (1.04)	-0.09 (-1.51)	0.08 (0.69)	-0.10 (-1.10)
USA(12) ->	EUR(12)	0.53 (2.72)	0.01 (0.17)	0.16 (1.76)	-0.20 (-2.10)
USA(12) ->	JAP(12)	0.18 (0.90)	-0.10 (-1.66)	0.04 (0.39)	-0.21 (-1.65)
EUR (12) ->	JAP(12)	0.45 (1.75)	-0.02 (-0.25)	0.01 (0.13)	-0.12 (-1.17)

lios, the addition of a US based industry momentum strategy is advisable to improve his risk-return trade-off. The p-value for the coefficient a is 0.07, just below the significance level of 0.10. For the Japanese industry momentum strategy, no significant a is estimated (0.36, t-value 0.87), so this is not an attractive strategy for this investor. An industry momentum strategy for Europe seems to expand the investment opportunity set for this US investor significantly, with a risk-adjusted expected excess return of 0.83 (t-value 2.89). Interestingly, the lead-lag strategies which use US industries in the formation period and European and Japanese industries in the investment period both have a significantly positive expected excess return, which means that both strategies are attractive for a US investor who owns a combination of the three Fama-French portfolios.[15] The three risk factors do not seem to reduce the expected excess returns on momentum strategies, since most coefficients for the market factor and value factor are negative. It seems that industry momentum strategies are positively sensitive to the size factor (albeit not significant), indicating that the excess return is not driven by small stocks.

3.6 Conclusions

In this paper we confirm the existence of a medium term industry momentum effect for the US using Datastream indices. This result is a robustness check on earlier work by e.g. Moskowitz & Grinblatt (1999). The empirical evidence reported here indicates the existence of an industry momentum effect for Europe too, whereas industry momentum seems to be absent in Japan. Since we do not have individual stock data we cannot investigate whether industry momentum subsumes the individual momentum effect. Nevertheless, the level of expected returns for medium term momentum strategies indicate this is likely not to be the case. The raw expected returns for industry momentum portfolios are 0.44 percent in the US and 0.63 percent in Europe, about half the size of the individual momentum strategies reported in Jegadeesh & Titman (2001) and Rouwenhorst (1998). Since momentum is generally believed to be stronger among the small firms, the higher expected returns in the latter two studies might also be due to the equal weighting of stocks, while we use value-weighted industry indices.

The expected return on an industry momentum strategy in Europe and Japan can be increased by ranking US industries and subsequently investing in the international counterparts. The magnitude of returns stays the same for the European effect, but the volatility decreases. Furthermore, the industry momentum effect appears to be more long-lived, potentially reducing transaction costs when implementing such strategy. Interestingly, for

[15] A related paper by O'Neal (2000) claims that investors cannot use the sector mutual funds of their sample to exploit the US industry momentum effect once risk adjustments are made.

Japan the ranking on US industries generates a marginally insignificant 0.41 per month return on the medium term, which decays for longer formation or holding periods. Ranking on European industries instead results in both economically and statistically significant positive excess returns.

Finally, we show that our results are not driven by higher factor loadings on the unconditional Fama & French (1993) three factor model. This implies that the momentum effect is not a compensation for bearing risk on the market, size, or value factors. For a US investor who owns a combination of the three Fama-French portfolios, it seems advisable to invest in US and European industry momentum strategies. Additionally, the lead-lag portfolios also appear to be attractive. Most noticeable is the one-year strategy formed on US industries and invested in European industries, which generates a 6.4 percent annual risk corrected return. Since this strategy requires trading the industry portfolios only once each year, transactions costs are not expected to have a large impact on these results.

Chapter 4

Do countries or industries explain momentum in Europe?

4.1 Introduction

Stock return continuation on horizons between 6 and 12 months has been documented for the US, Europe, and emerging markets (see, e.g., Jegadeesh & Titman (1993), Rouwenhorst (1998), and Rouwenhorst (1999b), respectively). Several authors have recently investigated the sources of this stylized fact, also known as the momentum effect. The ambiguity in the empirical findings has kept the debate about the sources of the momentum effect lively. For example, Moskowitz & Grinblatt (1999) claim that industry effects are almost solely responsible for the momentum effect in the US, while Grundy & Martin (2001) report that industry momentum and individual stock momentum are distinct phenomena. In addition, a six-month momentum effect on a country index level is found by Chan et al. (2000), while Richards (1997) suggests there is no medium term country momentum effect. It is still an open question to what extent these findings on country momentum are related to differences in industry composition of the country indices. These issues are crucial in understanding the factors driving stock momentum and have direct implications for the performance of investment strategies. While the latter two papers focus on the momentum effect in an international context, the emphasis in the literature on the determinants of the momentum effect seems to have been predominantly directed to US stocks.

The aim of this chapter is to analyze medium term return continuation in Europe in further detail. In order to determine the source of the momentum effect in Europe, we develop a novel regression method which enables us to distinguish between individual stock, industry, and country effects. Our results provide evidence in the debate whether the individual stock momentum effect is subsumed by industry or country momentum effects. Our analysis of industry effects in Europe can be regarded as an out-of-sample test of hypotheses that have been formulated for US data. The simultaneous inclusion of country and industry effects sheds light on the influence of the industry composition of country indices that seems to have been neglected in the momentum literature so far.

In the analysis of US data, possible regional effects have received little attention. For Europe, regional effects such as country effects are clearly important; see e.g. Rouwenhorst (1999a). Their presence as well as the fact that for some country-industry combinations very few observations are available requires extensions of the existing methodology. Most analyses are based upon average returns within groups of stocks with similar characteristics. This sorting approach assumes that stocks with similar characteristics have identical conditional expected returns, while information regarding stocks with other characteristics is considered irrelevant. In this chapter, we present a novel regression approach that uses characteristics of a large variety of portfolios in order to estimate the expected returns on stocks with similar characteristics.

The regression-based approach is more convenient when we want to discriminate between multiple effects that may be operating simultaneously. It is more general than the sorting approaches, since it enables us to incorporate information about the characteristics of other portfolios into the estimation of the expected return of a particular stock. If one decides not to use this additional information, the regression approach reduces to the more familiar sorting methods. A major advantage of our regression approach is the possibility to distinguish between a large variety of effects by imposing a parsimonious structure on the model. The use of sorting methods in this context is limited, since sorting on multiple characteristics may lead to subportfolios with few or even no stocks. Furthermore, the regression approach easily allows for the incorporation of other effects, in addition to the individual, country, and industry effects. This is important, since several papers claim that expected returns on momentum strategies are related to firm size and book-to-market ratios.[1] In addition, the regression framework allows hypotheses about the relative importance of different effects to be formulated and tested in a more natural way than the sorting approach which basically compares average returns of sorted portfolios.

Our empirical results indicate that over the period 1990–2000 the individual component of the momentum effect is stronger than the industry component. In economic terms, individual momentum accounts for almost 60 percent of the total effect, while industries and countries explain about 30 and 10 percent, respectively. Our analysis suggests that a momentum strategy which is diversified with respect to countries and industries yields an expected excess return of about 0.55 percent per month. Incorporating value and size

[1]Examples of papers relating momentum to other characteristics are Hong et al. (2000), Chen (2000), and Nagel (2001).

effects in the model confirms that individual momentum dominates country and industry momentum effects. Moreover, the results indicate that momentum is most pronounced for small growth stocks.

This remainder of this chapter is organized as follows. In the next section, the portfolio-based regression approach is explained in detail. We show that by evaluating the composition of a large variety of diversified portfolios, sorted on the basis of relevant characteristics, one can determine which underlying factors are most important in explaining the momentum effect. Section 4.3 describes the data used throughout this chapter and provides some of its stylized facts. In Section 4.4, we analyze the question whether industry and country momentum exist, and whether they subsume individual momentum. The analysis is expanded by including size and value effects in Section 4.5. Finally, our conclusions are presented in Section 4.6.

4.2 A portfolio-based regression approach

The existing literature on stock selection is usually based on analyzing average returns of portfolios grouped on the basis of one or more characteristics. For example, extensive research has been done on the market capitalization (size), book-to-price ratio (value), and recent past returns (momentum) of firms. These characteristics may be related, and the excess return on portfolios of stocks that are grouped on certain characteristics are potentially subsumed by other characteristics. Thus, for investors it is important to investigate the additional value of sorting on another characteristic. In this chapter, we want to distinguish between country, industry, and individual momentum effects. In order to understand their interdependencies, it is important to consider a model that simultaneously allows for these effects. Unfortunately, increasing the number of sorts in a sorting context may dramatically reduce the number of stocks in each portfolio. As a result, idiosyncratic effects may dominate the returns of these portfolios, especially when the initial data set contains only a moderate number of stocks.

In our approach, we explain the returns of well-diversified portfolios using regression analysis. In such analysis, a multitude of effects can be distinguished by using the composition of portfolios, which are sorted on at most two characteristics. By using a portfolio-based regression technique it is possible to determine which of the effects is most important for the expected positive excess returns. For example, we investigate the relative importance of country, industry, and individual stock momentum on return continuation. While it is not always immediately clear how to develop meaningful test statistics when relying on sorting methods only, a variety of statistical tools can be used in a regression framework. Test statistics are readily available and well-understood in this context. Moreover, the use of a regression framework allows us to impose a natural (e.g. additive) structure on the model.

The use of portfolio-based regression techniques dates back at least to Roll (1992), who determines industry effects by a regression of country portfolios on the industry composition of these country portfolios. Other papers that use a regression approach are Heston & Rouwenhorst (1994) and Kuo & Satchell (2001). These two papers differ fundamentally from Roll (1992) and our chapter by the use of individual stock returns instead of well-diversified portfolio returns. None of the above papers allows for the presence of interaction effects between the factors. Moreover, the precise link with the frequently used sorting procedures is left unspecified. The methodology presented in this chapter fills these gaps.

As mentioned before, most empirical research is based on tests of differences in expected returns of portfolios that are based on sorting stocks on certain characteristics. For example, the seminal paper on the profitability of momentum strategies by Jegadeesh & Titman (1993) first ranks stocks on past six month return and subsequently divides the sample of stocks in ten portfolios with the same number of stocks. The returns of these portfolios are calculated over the subsequent six months. It turns out that the top decile ("winners") performs significantly better than the bottom decile ("losers").

When the influence of two characteristics is investigated, we could use a double sort or a two-way sort. A double sort means that the stocks are first ranked on one characteristic and independently sorted on another. The first portfolio then consists of stocks that are in the bottom in both the first and second sort. This way of sorting is for example used in Lee & Swaminathan (2001), where the characteristics are past returns and volume. Apart from this double sorting method, one can also use a conditional sort. Such a two-way sort means that the stocks are first ranked on a certain characteristic, after which a second sort is performed within the portfolios constructed after the first ranking. For example, Rouwenhorst (1998) first sorts the sample of stocks on size, and within these size deciles he forms momentum deciles. A notable difference between double sorting and two-way sorting is the importance of the order of sorting. For a double sort this is irrelevant, while two-way sorting can be highly sensitive to the order in which the sorts take place, especially when the characteristics are related.[2] We use the double sorting method to create cross-effects later on in the chapter, while two-way sorting is used in order to create country-neutral value and size portfolios.

A disadvantage of the two-way sorting approach is the limited applicability when more than two characteristics are subject of investigation, especially when the total number of stocks is moderate. When the number of sorts increases, the number of stocks per portfolio

[2]The terminology double sort and two-way sort is used for both unconditional and conditional sorts in different papers. To avoid confusion we reserve double for unconditional and two-way for conditional sorting.

will reduce rapidly. Hence, idiosyncratic firm effects will have much more influence on the average returns of such portfolios. To alleviate this problem researchers are often forced to work at a higher level of aggregation by using quintiles or tertiles (i.e. divide the sample in five or three parts) rather then deciles. This is illustrated by e.g. Davis, Fama & French (2000), who note that "the advantage of fewer third-pass sorts [...] is that the resulting 27 portfolios always contain some stocks [...] In 1930 and 1931, few portfolios have only one stock." This remark makes clear that to prevent empty subportfolios the number of sorts has to be reduced when only three characteristics are considered. The consequence of this type of solution is that effects which are most pronounced in the extreme deciles are much harder to detect empirically.

In similar spirit to the characteristics-based asset pricing model of Daniel & Titman (1997), we assume that the conditional expected return on a single stock can be modeled as a function of several effects. While the number of factors is arbitrary, we present the model with three factors, labeled A, B and C. Thus, we assume

$$\mathrm{E}_t\{R_{i,t+1}\} = \sum_{a=1}^{N_A}\sum_{b=1}^{N_B}\sum_{c=1}^{N_C}\alpha_{a,b,c}X_{i,t}\left(a,b,c\right), \tag{4.1}$$

where $X_{i,t}(a,b,c)$ is a dummy variable to indicate whether the stock is in a particular portfolio, and $R_{i,t}$ is the return of stock i in period t. The function $\mathrm{E}_t\{.\}$ denotes the expectation conditional on information up to (and including) period t. This information only consists of the set of dummy variables $X_{i,t}$, or in words, the portfolio a stock belongs to in period t. The parameter $\alpha_{a,b,c}$ is the expected return on a stock with characteristics a, b, and c. For example, if a stock belongs to the worst performing countries, industries, and individual stocks, its expected return would be $\alpha_{1,1,1}$. Basically, the sample of stocks is divided into cells, each of which represents a group of stocks with similar characteristics. The model simply describes the expected return of an arbitrary stock given that it is known to belong to a particular group.[3]

In our analyses, we prefer modeling the expected return of well-diversified portfolios instead of individual stocks. The advantage of the absence of idiosyncratic effects in well-diversified portfolios compensates for the potential loss of information by modeling at a more aggregated level. Additional arguments to use portfolios instead of individual stock data are the absence of missing observations when portfolios are used, and the reduced influence of poor quality data. Value-weighting the stocks in the portfolios of the regression

[3]One advantage of the regression-based approach, in contrast to sorting, is the possibility to include more precise information about the different factors than just quantile values. For example, one could model portfolio returns as a function of previous 6-month returns in deviation from the median. Given that the use of decile ranks is common in studies based on sorting, we do not pursue this possibility in this chapter.

weakens the impact of these data errors even further, since the reliability of stock data seems to be inversely related to firm size. The expected return on a portfolio p of N stocks with weights $w_{i,t}^p$, conditional on information up to and including period t, can be written as

$$\begin{aligned} \mathrm{E}_t\left\{R_{t+1}^p\right\} &= \mathrm{E}_t\left\{\sum_{i=1}^{N} w_{i,t}^p R_{i,t}\right\} \\ &= \sum_{i=1}^{N} w_{i,t}^p \mathrm{E}_t\left\{R_{i,t}\right\} \\ &= \sum_{a=1}^{N_A}\sum_{b=1}^{N_B}\sum_{c=1}^{N_C} \alpha_{a,b,c} X_t^p\left(a,b,c\right), \end{aligned} \tag{4.2}$$

where $X_t^p(a,b,c) \equiv \sum_{i=1}^{N} w_{i,t}^p X_{i,t}\left(a,b,c\right)$ denotes the holdings of portfolio p in categories (portfolios) $a, b,$ and c. This model expresses the expected return on a portfolio as a weighted average of the expected returns of its stocks.

In order to estimate equation (4.2), we can formulate it as a regression equation

$$R_{t+1}^p = \sum_{a=1}^{N_A}\sum_{b=1}^{N_B}\sum_{c=1}^{N_C} \alpha_{a,b,c} X_t^p\left(a,b,c\right) + \varepsilon_{t+1}^p, \tag{4.3}$$

where $\varepsilon_{t+1}^p \equiv R_{t+1}^p - \mathrm{E}_t\left\{R_{t+1}^p\right\}$ is uncorrelated with the regressors by construction. Moreover, cross-autocorrelations are zero, i.e. $\mathrm{E}\left\{\varepsilon_{t+h}^p \varepsilon_t^q\right\} = 0$, for each $p, q, t,$ and $h > 0$. No assumptions are made on the absence of heteroskedasticity or contemporaneous correlation.

As long as the number of portfolios used as dependent variables P is at least as large as the number of effects $N_A \cdot N_B \cdot N_C$, the unknown parameters can be estimated consistently using the Fama-MacBeth estimator. In other words, consistent estimates can be obtained by first performing cross-sectional regressions using OLS, followed by averaging these cross-sectional estimates over time. The sample covariance matrix of these cross-sectional estimates serves as an estimator for the true covariance matrix. This regression-based approach is numerically equivalent to computing average returns and sample standard deviations of sorted portfolios when these are sorted upon exactly the same characteristics as the regressors X_t^p. Thus, our method reduces to the traditional sorting approach in this special case.[4]

Since the number of parameters in (4.3) may become large, a more parsimonious way to describe the expected returns on the portfolios is desirable. This is particularly fruitful

[4]It can be shown that this still holds when portfolios are added that contain no new information about the effect under investigation.

when the number of sorts or the number of groups within a sort is increased. By imposing structure on the model the number of parameters can be reduced, and hence the efficiency of the estimators can be increased. For example, in line with Roll (1992) and Heston & Rouwenhorst (1994) an additive structure can be imposed. In order to see how the regression equation in (4.3) is affected by this assumption, rewrite equation (4.2) as

$$\begin{aligned}
\mathrm{E}_t\{R_{t+1}^p\} = {} & \alpha_{1,1,1} + \sum_{a=2}^{N_A} \beta_a^A X_t^p(a,\cdot,\cdot) + \sum_{b=2}^{N_B} \beta_b^B X_t^p(\cdot,b,\cdot) + \sum_{c=2}^{N_C} \beta_c^C X_t^p(\cdot,\cdot,c) + \\
& + \sum_{a=2}^{N_A}\sum_{b=2}^{N_B} \gamma_{a,b}^{AB} X_t^p(a,b,\cdot) + \sum_{a=2}^{N_A}\sum_{c=2}^{N_C} \gamma_{a,c}^{AC} X_t^p(a,\cdot,c) + \sum_{b=2}^{N_B}\sum_{c=2}^{N_C} \gamma_{b,c}^{BC} X_t^p(\cdot,b,c) + \\
& + \sum_{a=2}^{N_A}\sum_{b=2}^{N_B}\sum_{c=2}^{N_C} \delta_{a,b,c} X_t^p(a,b,c).
\end{aligned} \tag{4.4}$$

The dots in the holding arguments, for example in $X_t^p(a,\cdot,\cdot)$, denote that only the first argument is considered. This means that it refers to the number of stocks that are in group a, irrespective of their position in the other two sorts. The parameter $\alpha_{1,1,1}$ denotes the return on the reference portfolio, which we arbitrarily chose to be the one corresponding to $a = 1$, $b = 1$, and $c = 1$.[5] The other parameters on the first line (denoted β) account for the effects of being in another portfolio than the reference portfolio. The parameters in the second line represent the first-order cross-effects, and those in the third line refer to second-order cross-effects. These first-order cross-effects quantify the additional expected return above the sum of the effects in the first line due to an interaction between two of the effects. For example, a stock in the winner country and in the winner individual portfolio might have a higher expected return than just the winner country momentum effect plus the winner individual effect. A similar reasoning applies for second-order effects which account for interaction between all three effects.[6]

When we decide to impose an additive structure on the model in equation (4.4), this implies that all parameters γ and δ are assumed to be zero. Thus, first and higher-order interaction effects are neglected, which implies that the expected returns of cells are related by a simple structure. This way, information from cells that are close to each other may be exploited to obtain more efficient estimates. Imposing the additive structure leads to a substantial reduction of the number of parameters and hence gives more efficient estimates if the restrictions are valid. However, this gain in efficiency may be offset by

[5] Alternatively, it is possible to replace the reference portfolio by symmetric restrictions to avoid the dummy trap. Doing so changes the interpretation of the coefficients, but it does not change the statistical properties of the model. The advantage of our setup is that one can immediately observe the significance of the difference between the expected returns of winner and loser stocks.

[6] The parameters of equation (4.4) can straightforwardly be expressed in terms of those of equation (4.2).

the introduction of a bias when the imposed restrictions are not in accordance with the data. Therefore, it is relevant to perform a test on the validity of the restrictions. A Wald-test can be conducted in order to evaluate the hypothesis that all interaction effects, or a subset of them, are jointly zero.

Once the model structure is parsimoniously chosen, the relevant question about the relative importance of the three effects can be investigated. Suppose that the three effects separated are country (A), industry (B), and individual (C) momentum effects. Assuming that the additive structure is appropriate, the reduced form of the expected return of a portfolio can be rewritten as

$$\mathrm{E}_t\{R^p_{t+1}\} = \alpha + \sum_{a=2}^{N_A} \beta^A_a X^p_t(a,\cdot,\cdot) + \sum_{b=2}^{N_B} \beta^B_b X^p_t(\cdot,b,\cdot) + \sum_{c=2}^{N_C} \beta^C_c X^p_t(\cdot,\cdot,c), \tag{4.5}$$

where α is the expected return on the reference portfolio. The parameters β^A, β^B, and β^C can then be interpreted as the additional expected return for being in another momentum portfolio than the reference portfolio. For analyzing the sources of the momentum effect, we can now formulate and test hypotheses on the values of these parameters. For example, a test on the significance of the parameters $\beta^C_{N_C}$ gives information about the importance of being in the winner individual decile relative to being in the loser decile, conditional on the industry and country momentum portfolios the stock is in.

The momentum effect is typically investigated by looking at the return difference between the extreme deciles. Incorporating knowledge about the expected return on other deciles might help to get a more reliable estimate of the momentum effect. In order to support this idea, a parametric structure on the expected returns of the deciles can be imposed. For example, using a low-order polynomial reduces the number of parameters, and hence further increases the parsimony of the model. Therefore, the restriction that we add to (4.5) is

$$\beta^C_c = \lambda_0 + \lambda_1 \cdot c + \ldots + \lambda_L \cdot c^L,$$

where L is the order of the polynomial.[7] As a result, equation (4.5) changes to

$$\mathrm{E}_t\{R^p_{t+1}\} = \sum_{a=2}^{N_A} \beta^A_a X^p_t(a,\cdot,\cdot) + \sum_{b=2}^{N_B} \beta^B_b X^p_t(\cdot,b,\cdot) + \sum_{\ell=0}^{L} \lambda_\ell Z^p_t(\ell), \tag{4.6}$$

where $Z^p_t(\ell) \equiv 1 + \sum_{c=2}^{N_C} \left(c^\ell - 1\right) X^p_t(\cdot,\cdot,c)$. When this additional restriction is imposed, the existence of a momentum effect can be tested by using the return information of all deciles instead of just the winner and loser portfolio. In Section 4, the above models are used

[7]In this case, it is natural to also impose that $\alpha = \lambda_0 + \ldots + \lambda_L$.

in an empirical application to gauge the importance of country, industry, and individual stock momentum on return continuation for European stocks. By disentangling these three effects, we aim to find the driving force(s) behind the momentum effect. In Section 5, we also incorporate value and size effects in our analysis. This way, we allow for the possibility that certain momentum effects are explained by their value or size characteristics.

4.3 Data

Our focus is on large European stocks. The main reason for this choice is that reliable European data for smaller stocks are hardly available. For instance, stock splits are sometimes not accounted for appropriately. Our sample period comprises 131 months, from January 1990 to November 2000 and initially contains all stocks from the moment they are covered by analysts from Morgan Stanley Capital International (MSCI). Note that analyst coverage does not imply that the stocks are present in any of the MSCI indices.[8] We require stocks to have information available on their six month return, market value, and book-to-market ratio. All returns and market values have been converted into Deutschemarks (DEM).

The underlying sample consists of 1581 stocks in total. These stocks have their major listing on the stock exchange of either Italy, Denmark, Ireland, France, Sweden, Finland, UK, Spain, The Netherlands, Norway, Germany, Portugal, Belgium, and Austria.[9] The number of firms per country varies from 33 for Ireland to 349 for the UK. In total 6 of the 15 countries contain less than 50 stocks, while 4 countries have more than 150. The differences in the number of firms per country has implications for the potential diversification benefits that can be obtained within a country. A list of countries with descriptive statistics can be found in Table 4.1. Finland is the only country with a value-weighted average monthly return exceeding 2 percent, while Austria and Norway are the only countries with an average below 1 percent (0.23 and 0.80 percent, respectively). Finland is most volatile with a monthly standard deviation of 9.1 percent, and The Netherlands is the least volatile with 4.5 percent. Equally weighting gives similar results.

Classifying firms in industries is less clear cut than the country division. First, it is not clear which and how many industries should be distinguished. Second, many firms are operating in several businesses, which makes it difficult to determine to which industry they primarily belong. For US studies, the SIC is the dominating classification, with appropriate regrouping as proposed in e.g. Moskowitz & Grinblatt (1999). This regrouping does not work well for European stocks, since several industries would contain few or no

[8]The returns are obtained from the *Prices* database through Factset. The data on market values and book-to-price ratios are obtained from the *Worldscope* database.

[9]The selection procedure resulted in one stock listed in Luxembourg. This stock has been deleted.

Table 4.1: **Monthly returns and standard deviations per country in percent per month, January 1990 – November 2000.** The first columns represents value-weighted country portfolios, while the second is equally-weighted. The next column shows the total number of stocks per country portfolio (and a comparison with the number of firms in the sample from Rouwenhorst 1998). The last three columns contain the average returns on the momentum, size, and value portfolio per country, measured by the excess return on the "winner" minus "loser" deciles/tertiles on these three characteristics. The portfolios are based on the average of the past six months (for all characteristics), and subsequently held over the next six month. In order to reduce market microstructure effect, the first month is skipped between portfolio formation and investment. Significance at the 90% and 95% level is indicated with * and **, respectively.

	value weighted		equally weighted		number			
Country	mean	std dev	mean	std dev	of firms	mom	size	value
Italy	1.13	8.5	1.16	8.7	176	0.30	0.31	-0.30
Denmark	1.14	5.1	1.07	4.8	49	**1.60	0.09	0.24
Ireland	1.11	6.1	0.81	6.0	33	0.98	-0.66	-0.73
France	1.24	5.4	1.26	5.0	165	*0.75	0.36	-0.16
Sweden	1.65	7.1	1.41	6.9	96	-0.59	-0.15	-0.04
Finland	2.02	9.1	1.36	8.0	43	1.21	-0.33	-1.47
UK	1.26	4.9	1.45	5.3	349	*0.87	**1.22	-0.27
Spain	1.14	6.7	0.91	7.1	91	0.20	-0.63	**1.35
Switzerland	1.37	4.8	1.41	4.9	140	0.35	0.42	**1.17
The Netherlands	1.58	4.5	1.43	4.5	67	0.61	-0.30	0.58
Norway	0.80	7.3	1.25	7.8	47	0.29	1.59	0.94
Germany	1.03	5.4	0.71	4.4	171	0.71	**-1.07	-0.72
Portugal	1.00	5.9	0.98	5.8	66	1.03	0.43	-0.72
Belgium	1.26	5.0	1.03	4.8	42	0.61	**-0.94	-0.42
Austria	0.23	6.7	0.34	6.4	46	-0.09	0.89	**1.83

Table 4.2: **Monthly returns and standard deviations per industry in percent per month, January 1990 – November 2000.** The first columns represents value weighted industry portfolios, while the second is equally weighted. The next column shows the total number of stocks per industry portfolio. The last three columns contain the average returns on the momentum, size, and value effect per industry, measured by the excess return on the "winner" minus "loser" deciles/tertiles on these three characteristics. The portfolios are based on the average of the past six months (for all characteristics), and subsequently held over the next six month. In order to reduce market microstructure effect, the first month is skipped between portfolio formation and investment. Significance at the 90% and 95% level is indicated with * and **, respectively.

	value weighted		equally weighted		number			
Industry	mean	std dev	mean	std dev	of firms	mom	size	value
Energy	1.38	5.4	1.27	5.7	34	0.26	0.53	**1.55
Materials	0.86	5.3	0.82	5.4	199	-0.04	-0.43	0.83
Capital Goods	0.71	5.5	0.86	5.4	260	0.07	0.23	0.78
Commercial Services & Supplies	0.74	5.7	1.03	5.2	80	**1.91	0.39	-0.23
Transportation	0.91	5.4	0.95	5.1	59	0.17	0.46	-0.33
Automobiles & Components	0.59	7.1	1.05	6.5	32	-0.51	*1.30	-0.14
Consumer Durables & Apparel	1.45	6.1	1.00	5.3	68	1.27	-0.65	0.08
Hotels, Restaurants, & Leisure	0.69	6.2	1.21	5.8	25	**1.48	**1.58	-0.24
Media	1.55	6.7	1.84	6.7	57	0.89	**1.73	0.59
Retailing	0.97	4.7	1.08	4.5	70	*0.91	0.69	-0.37
Food & Drug Retailing	1.24	4.7	1.23	4.3	27	*0.98	0.84	0.46
Food, Beverages, & Tobacco	1.23	4.4	0.98	4.0	86	0.87	-0.48	0.42
Household & Personal Products	1.83	5.9	1.29	5.4	9	0.51	-1.07	1.38
Health Care Equipment & Services	1.60	6.1	1.53	4.8	35	0.54	0.70	0.23
Pharmaceuticals & Biotechnology	1.69	4.5	2.00	4.1	30	*1.30	1.01	0.33
Banks	1.40	5.7	1.44	5.3	125	0.22	-0.34	*1.23
Diversified Financials	1.29	5.6	1.45	5.2	64	1.01	-0.05	-0.01
Insurance	1.25	5.2	1.20	5.1	123	0.40	-0.23	0.04
Real Estate	0.62	5.1	0.71	4.8	28	0.08	-0.18	0.88
Software & Services	2.55	9.5	3.11	8.9	31	0.44	2.04	0.16
Technology Hardware & Equipment	2.03	8.5	2.49	7.5	24	**2.51	1.33	-1.70
Telecommunication Services	1.82	7.0	2.15	7.8	44	0.80	0.96	0.98
Utilities	1.19	4.1	1.44	4.1	71	-0.40	0.52	0.84

stocks at all. Therefore, we use the classification in MSCI industries, which aggregates the stocks in 23 industries.[10] The number of firms per industry varies between 9 and 260. In total, 10 out of 23 industries contain less than 50 stocks, while 4 have more than 100. An overview of the industries with descriptive statistics is presented in Table 4.2. The lowest value-weighted average return is for the industry Automobiles (0.59 percent), while the highest average returns are for Software and Services (2.55 percent). The latter has the highest standard deviation (9.5 percent). The least risky in absolute terms is the industry Utilities with a monthly standard deviation of 4.1 percent. Equally-weighted industry returns are close to their value-weighted counterparts.

We consider the 6-month momentum trading strategy proposed in Jegadeesh & Titman (1993), where a six month evaluation period is used combined with a six month holding period. In each month, the stocks are ranked in descending order on their (total) return over the last six months. In the next step, ten portfolios with the same number of stocks are formed. Ranking takes place each month, independently of the holding period. In each month, the ten decile portfolios consist of a portfolio selected in the current month, as well as the five portfolios formed in the previous five months. The top and bottom deciles are called winner and loser portfolio, respectively. A W–L strategy takes a long position in the winner portfolio and a short position of equal size in the loser portfolio. The excess return on this zero investment strategy is defined as the return on the winner minus the return on the loser portfolio.

The stocks from our database are sorted according to their prior six month return, book-to-price ratio, and market value to obtain the momentum, value, and size portfolios. In addition, we created three country and three industry momentum portfolios. The winner industry portfolio consists of all stocks listed in the top four industries. The loser industry and middle industry portfolio consist of four and fifteen industries, respectively. We construct the country momentum portfolios similarly. So, the winner and loser country portfolio consist of four countries, while the middle country portfolio contains seven.

Throughout, when a stock is delisted, the residual claim is assumed to be invested in cash with zero return for the remainder of the holding period.[11] No data are available to determine the reason for delisting, so the actual final payment cannot be taken into account when reproducing the strategy's returns. However, we expect that this does not

[10]The MSCI industry classification is new as of 2000, such that several delisted firms had to be manually reclassified from the older classification. This has been done with the help of ABP Investments and MSCI. The actual classification used is available upon request. Firms that switch across industries over time will be classified by their final industry membership, which is the only data available to us. However, we expect this to have only minor influence on the results, as reported for US data by Moskowitz & Grinblatt (1999).

[11]This deviates from the methodology in Rouwenhorst (1998). If a firm goes bankrupt the treatment is identical, but not in case of a merger/takeover. Rouwenhorst invest the proceeds in the merged firm or the target. Unfortunately, we do not have data on the reason of delisting, neither on the identity of the merged firm or target.

lead to a positive bias in our results. When a firm is delisted because of bankruptcy, this typically results in a large negative final return that is not accounted for in the database. However, these firms tend to be among firms with low past performance, and consequently have higher probability of being among the losers. The omission of the final returns in the database overestimates the actual return on the loser portfolio, hence decreases the return on strategies with short positions in the loser firms. This suggests that our results are conservative. Furthermore, delisting through bankruptcy does not occur frequently for large firms. Takeovers and mergers are usually more important reasons for delisting; see Wang (2000) for a more extensive treatment on the topic of delisting.

Before we turn to a decomposition of the momentum effect, we investigate the presence of momentum, value, and size effects within countries and industries. In Table 4.1 and Table 4.2 we observe no clear value or size effect within individual countries or industries in our sample.[12] For example, during 1990-2000, the UK is the only country with a significant size effect, which has an expected excess return of 1.22 percent per month. In Germany and Belgium, the opposite effect is found, i.e. stocks with a large market capitalization have outperformed small cap stocks. The value effect appears to be present in Spain, Switzerland, and Austria. For the industries Hotels, Restaurants, and Leisure, and Media, we find a significant size effect, while the value effect (1.55 percent) is present in Energy. For most countries and industries the excess return on the momentum portfolio is positive and economically relevant, albeit statistically significant only in a few cases. A country-neutral momentum strategy, which means that the winner and loser portfolios are averaged over each of the countries, yields a significant 0.63 percent (t-value 2.20). In similar fashion we calculate an industry-neutral momentum return, which is even higher with 0.81 percent (t-value 2.66).

4.4 Do countries or industries explain momentum?

In this section, the portfolio-based regression technique described in Section 2 is used to determine the relative importance of country, industry, and individual momentum effects on the total momentum effect in Europe. We use a set of 196 portfolios to disentangle the momentum effect into a country, industry, and an individual stock momentum effect. The portfolios used to evaluate the momentum effect are sorted on these three momentum factors complemented with size and value. In total, we have 16 momentum portfolios: the 10 individual, 3 country, and 3 industry portfolios, as described earlier. We rank each stock on their average market capitalization over the past 6 months, and divide the sample

[12]In Heston, Rouwenhorst & Wessels (1999), it is shown that the size effect for European stocks is non-linear in the sense that it is restricted to the smallest three deciles of their sample, which covers many more firms than our sample. The fact that we do not find a size effect is consistent with their results.

in three parts. Creating value portfolios only changes the ranking variable to the average book-to-price ratio of the stock. The size and value portfolios are country-neutral, which means that the same fraction of the stocks from each country is represented in these portfolios. For example, the "winner" value portfolio consists of the top 33% of value stocks from Austria, the top 33% of value stocks from Belgium, etcetera. In order to create double-sorted portfolios, we combine the single rankings from above. For example, the individual winner/country winner portfolio consists of all stock that are in the individual winner portfolio and in the country winner portfolio. The number 196 is obtained as the sum of 22 single-sorted and 174 double-sorted portfolios.[13] To reduce the influence of small stocks on the outcome of the analysis all portfolios are value-weighted. The regressors in equation (4.3) are the holdings of these evaluation portfolios in the effects of interest. These holdings are, like the returns, value-weighted within each portfolio.

In order to determine the momentum effect in our sample, we evaluate the 196 portfolios from our test set. In this case only the holdings of these portfolios in the momentum decile portfolios are used to explain the corresponding portfolio returns. More precisely, we estimate the regression equation

$$R^p_{t+1} = \alpha + \sum_{a=2}^{10} \beta_a^{MOM} X_t^p(a) + \varepsilon^p_{t+1}, \tag{4.7}$$

where $X_t^p(a)$ denotes the holdings of portfolio p in momentum decile a for period t, by using the Fama-MacBeth estimator. Instead of ordinary least squares (OLS) we use a weighted least squares (WLS) estimator, where the weights are the (square root of the) number of stocks in a portfolio. By using this weighting scheme portfolios with a small number of stocks are considered less important than portfolios with a large number of stocks. The loser portfolio is chosen to be the reference portfolio.

The estimates for equation (4.7) using our sample of European stocks from 1990-2000 are reported in Table 4.3. The existence of a momentum effect in Europe for the last decennium can be investigated by performing a t-test on β_{10}^{MOM}, which denotes the expected return on the winner portfolio relative to the loser portfolio. The results indicate that a momentum effect is present in Europe during the last 10 years, albeit statistically insignificant at the 95% level (p-value 0.11).[14] Both the confidence level and the level of the excess return is somewhat below the values reported in Jegadeesh & Titman (1993) and Rouwenhorst (1998). This can be partly explained by the length and coverage of our

[13]Double-sorting on individual momentum and each of the other four factors produces $10 \cdot 12 = 120$ portfolios. Double-sorting on each combination of the other four factors accounts for the remaining $\binom{4}{2} \cdot (3 \cdot 3) = 54$ portfolios in the analysis. Some intersections contain no stocks and result in missing observations for a small number of periods.

[14]This result is qualitatively the same as the one obtained from the traditional sorting analysis.

Table 4.3: **Momentum effect in Europe, January 1990 – November 2000.** Results for the portfolio-based regression $R^p_{t+1} = \alpha + \sum_{a=2}^{10} \beta_a^{MOM} X_t^p(a) + \varepsilon^p_{t+1}$, with 196 evaluated portfolios. The portfolios are based on sorts and double-sorts on characteristics country, industry, and individual momentum, value, and size. The first set of results is based on the Fama-MacBeth estimator with cross-sectional WLS, with the square root of the number of stocks per portfolio as weights. The second set of results is calculated with the cross-sectional OLS. The rows indicated with "est" contain the estimates (expected return in percentage per month), and the rows with "t-val" the t-values corresponding to the estimate above it.

		α	β_2^{MOM}	β_3^{MOM}	β_4^{MOM}	β_5^{MOM}	β_6^{MOM}	β_7^{MOM}	β_8^{MOM}	β_9^{MOM}	β_{10}^{MOM}
WLS	est	1.13	0.07	0.19	0.27	0.21	0.34	0.40	0.46	0.54	0.79
	t-val	2.00	0.38	0.82	1.01	0.68	1.00	1.05	1.16	1.20	1.59
OLS	est	1.14	0.09	0.23	0.28	0.23	0.33	0.37	0.47	0.52	0.81
	t-val	2.10	0.55	1.13	1.20	0.84	1.11	1.14	1.35	1.34	1.84

data set. Since our sample comprises only 10 years, t-values are lower even when means and standard deviations are identical to those for the US.[15] Our data set covers only the larger funds, and there is empirical evidence indicating that momentum profits are weaker for larger stocks; see e.g. Rouwenhorst (1998), and Hong et al. (2000). The latter study claims that there is no excess return of winners over losers in the US when the largest market cap quintile is considered.[16] Summarizing, our results on the momentum effect in Europe are in line with the existing literature.

Next, we impose a polynomial structure on the expected returns of the different momentum deciles, along the lines described in Section 2. The results, reported in Table 4.4, for different orders of the polynomial, indicate that the polynomial structure does not help to obtain more precise statements about the presence and magnitude of the momentum effect. The results for polynomials of order three and four are virtually the same as unrestricted estimates reported in Table 4.3.

The main motivation for this chapter is to see whether the total momentum effect in Europe is subsumed by momentum effects on a higher level of aggregation, i.e. country and industry momentum. To analyze this, we return to the general model in equation (4.4). With three country momentum, three industry momentum, and ten individual

[15]We could also use a measure which is not depending on the length of the sample period, e.g. the information ratio (IR). This measure is defined as the expected return divided by the standard deviation. The IR from our value- weighted momentum strategy equals 0.15. In Rouwenhorst (1998) the IR is 0.15 for the largest equally weighted size decile, in Hong et al. (2000) each of the top three size deciles has an IR below 0.14.

[16]The largest quintile is based on NYSE/AMEX breakpoints and consists of about 400 to 500 stocks at each date. The claim of a non-existing momentum effect for these stocks is based on the use of tertile portfolios sorted on past six month returns instead of decile portfolios, which is more common in this line of research.

Table 4.4: **The momentum effect in Europe by imposing polynomials on the decile structure, January 1990 – November 2000.** Estimation results for the estimates of the regression equation $R^p_{t+1} = \sum_{l=0}^{L} \lambda_l Z^p_t(l) + \eta^p_{t+1}$, where $Z^p_t(l) \equiv 1 + \sum_{a=2}^{N_A} \left(a^l - 1\right) X^p_t(a)$. The regression equation is evaluated for a third-order polynomial, i.e. $L = 3$. In panel A the results for the hyperparameters are presented, while in panel B these parameters are converted into expected returns for the deciles. For the sake of completeness, the result without fitting the third-order polynomial are also presented in panel B in the row labelled "no".

A	λ_0	λ_1	λ_2	λ_3	λ_4
est	1.037	0.078	0.011	-0.004	0.000
t-val	1.35	0.19	0.09	-0.23	0.37
est	0.942	0.198	-0.033	0.002	–
t-val	1.43	1.03	-0.95	1.04	–
est	1.14	0.026	0.004	–	–
t-val	1.80	0.20	0.39	–	–

B		α	β_2^{MOM}	β_3^{MOM}	β_4^{MOM}	β_5^{MOM}	β_6^{MOM}	β_7^{MOM}	β_8^{MOM}	β_9^{MOM}	β_{10}^{MOM}
No	est	1.13	0.07	0.19	0.27	0.21	0.34	0.40	0.46	0.54	0.79
	t-val		0.38	0.82	1.01	0.68	1.00	1.05	1.16	1.20	1.59
$L = 2$	est	1.17	0.04	0.09	0.14	0.21	0.28	0.36	0.46	0.56	0.66
	t-val		0.39	0.48	0.59	0.72	0.87	1.03	1.21	1.36	1.46
$L = 3$	est	1.11	0.12	0.19	0.24	0.29	0.33	0.39	0.47	0.60	0.79
	t-val		0.99	0.97	0.96	0.96	1.00	1.09	1.24	1.44	1.59
$L = 4$	est	1.12	0.09	0.17	0.23	0.28	0.33	0.37	0.45	0.57	0.78
	t-val		0.58	0.75	0.88	0.96	1.00	1.03	1.12	1.31	1.59

momentum effects, the total number of unknown parameters in this model is equal to 90. When an additive structure is imposed, as in equation (4.5), the parsimony of the model is highly increased, and the number of parameters is reduced to only 14.[17] The intuition behind imposing an additive structure is that the effects are the same for all portfolios (or stocks) conditional upon all other characteristics incorporated into the model. In other words, the individual momentum effect is not different for stocks that are listed in a loser country compared to stocks that are listed in a winner country. This does not mean that the country of listing does not influence the expected return of the stocks. In an additive model it just does so independently from the individual and industry effect. Of course, this simplified additive model specification is tested before continuing the analysis. Without proper tests to identify the validity of these restrictions biased parameters estimates might be obtained and hence inferences could be erroneous. Testing the additivity constraints is lacking in most previous papers. The results from the Wald-test indicate that imposing additivity is allowed. The test statistic of 37.3 is well below the 90%-critical value of 47.2.[18]

The regression equation for the additive model we use to distinguish country, industry, and stock momentum is

$$R_{t+1}^p = \alpha + \sum_{a=2}^{3} \beta_a^{COU} X_t^p(a, \cdot, \cdot) + \sum_{b=2}^{3} \beta_b^{IND} X_t^p(\cdot, b, \cdot) + \sum_{c=2}^{10} \beta_c^{STOCK} X_t^p(\cdot, \cdot, c) + \varepsilon_{t+1}^p. \quad (4.8)$$

From the estimation results in Table 4.5, we can infer the influences on the expected returns of a stock being in specific momentum portfolios. The expected future return of a stock can be determined given the information about the current groups this stock belongs to. In the case of an additive model, this involves summing the expected returns of each of the components. For example, the expected return of a stock that is in the group of best four countries, in the middle industries, and in the winning individual decile has an expected return of 1.86 percent per month. This number consists of the return on the reference portfolio (1.13) plus the country winners (0.12) plus the industry middle (0.06) plus the individual winner (0.55). The expected returns for all other combinations can be obtained in similar fashion. See Figure 4.1 for a graphical representation of these results. There is a clear gradual increase in the expected return by moving from the front to the back of the figure. This suggests that momentum investors who are interested in a

[17] Due to the additive structure, perfect multicollinearity would result by including $10 + 3 + 3 = 16$ effects. See the first line of equation (4.4) to obtain the $1 + 2 + 2 + 9 = 14$ free parameters in the model. The first-order interaction effects account for $4 + 18 + 18 = 40$ parameters, and the second-order effects for the remaining 36.

[18] We test the hypothesis that all cross-terms are jointly zero by performing a Wald-test. The p-value associated with the reported test is 0.407. Calculating the Fama-MacBeth estimator with OLS instead of WLS results in a p-value of 0.135, still not rejecting the null hypothesis of the absence of cross-effects.

Figure 4.1: **Expected excess returns for stocks in country, industry, and individual stock momentum portfolios in Europe, January 1990 – November 2000.** Excess returns are defined relative to the reference portfolio of stocks in the loser country, loser industry, and loser individual momentum portfolio. The x-axis of this figure contains the individual momentum deciles, the y-axis the country-industry combinations, and the z-axis the monthly expected excess return relative to the reference portfolio (individual loser, country loser, and industry loser). The acronyms used are country (COU), industry (IND), and winner (W), middle (M), and loser (L).

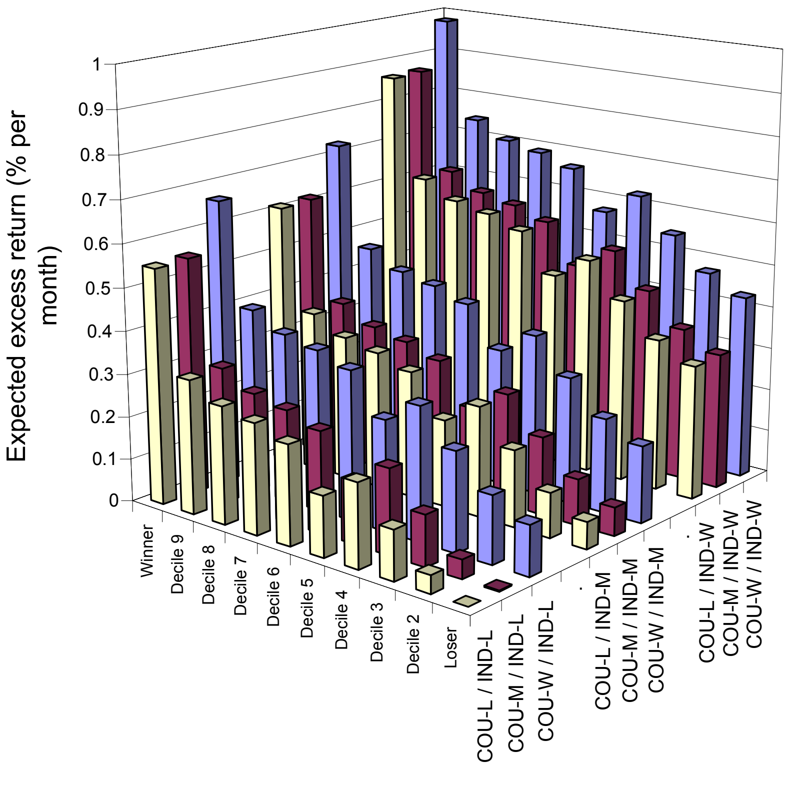


Table 4.5: **The momentum effect in Europe decomposed in a country, industry, and individual stock momentum effect, January 1990 – November 2000.** Estimation results for the portfolio-based regression $R^p_{t+1} = \alpha + \sum_{a=2}^{3} \beta^{COU}_a X^p_t(a,\cdot,\cdot) + \sum_{b=2}^{3} \beta^{IND}_b X^p_t(\cdot,b,\cdot) + \sum_{c=2}^{10} \beta^{ST}_c X^p_t(\cdot,\cdot,c) + \eta^p_{t+1}$, with 196 evaluated portfolios. The portfolios are based on sorts and double-sorts on characteristics country, industry, and individual momentum, value, and size. The results are based on the Fama-MacBeth estimator with cross-sectional WLS. The rows indicated with "est" contain the estimates (expected return in percentage per month), and the rows with "t-val" the t-values corresponding to the estimate above it. The parameter α denotes the reference portfolio, parameter indicated with superscript COU, IND, and ST measure the country, industry, and individual stock momentum effect. The higher the subscript number, the higher the stock scored on that particular characteristic. See also Figure 4.1 for a graphical representation of these results.

WLS	α	β^{COU}_2	β^{COU}_3	β^{IND}_2	β^{IND}_3
est	1.13	0.00	0.12	0.06	0.31
t-val	1.84	0.01	0.38	0.47	1.31

	β^{ST}_2	β^{ST}_3	β^{ST}_4	β^{ST}_5	β^{ST}_6	β^{ST}_7	β^{ST}_8	β^{ST}_9	β^{ST}_{10}
est	0.04	0.12	0.19	0.14	0.23	0.26	0.27	0.31	0.55
t-val	0.23	0.55	0.80	0.52	0.80	0.81	0.85	0.87	1.44

high expected return should try to find stocks that are listed in European countries that performed well over the past six months, in industries that performed well over the last six months, and in the top decile that ranks European stocks on the basis of their individual past six month return.

The country momentum effect has contributed least to the momentum effect in Europe over the past decennium, with an additional expected return of 0.12 percent per month.[19] The industry momentum effect is weakly present with an additional expected return of 0.31 percent. The largest effect is individual momentum, which contributes roughly 0.55 percent over the reference portfolio. Consequently, the estimated expected excess return of a momentum strategy for stocks in the winner countries, winner industries, and individual winners is roughly 12 percent per year without transactions costs. With a maximum turnover of each stock of only twice a year, the break even transactions costs would be about 6 percent for a round-trip, which is much higher than the upper bound of 2 percent that is used in most empirical studies. Our estimation results suggest that the momentum effect based on individual stocks is not subsumed by industry momentum, country momentum, or both. This finding is consistent with Rouwenhorst (1998), who

[19] Although we consider a different group of countries than Richards (1997) and Chan et al. (2000), our results seem more in line with the former, who indicate there is only weak evidence of medium term return continuation at the country level, while the latter report a significant country momentum effect.

shows that the excess returns of country-neutral momentum strategies in Europe are only slightly lower than those of unrestricted momentum strategies. It is also in accordance with the results for the US stock market, reported in e.g. Grundy & Martin (2001), who state that individual momentum and industry momentum are separate phenomena. The conclusion that industry momentum drives the individual momentum effect in the US, reported in Moskowitz & Grinblatt (1999), is not supported by our empirical analysis for Europe. Our results indicate that investment professionals who are not allowed to take large country and industry bets might still be able to exploit the momentum effect by stock selection, although this reduces the potential expected return by almost a half.

4.5 The impact of value and size effects

The previous analysis ignores well-known effects such as value and size (see e.g. Fama & French (1992)). In this section, we expand the model in (4.8) to capture the potential relation between the value and size effect and the momentum effects. While a Wald-test previously indicated that the additive model specification is appropriate for (4.8), this is not the case for this larger model. The p-value corresponding to the hypothesis that cross-effects are jointly zero is less than one percent, which clearly rejects the additive model specification. We decide to add the cross-effects between momentum, size, and value to the model. The regression equation of the resulting model is given by

$$\begin{aligned} R^p_{t+1} = {} & \alpha + \sum_{a=2}^{3} \beta_a^{COU} X_t^p(a,\cdot,\cdot,\cdot,\cdot) + \sum_{b=2}^{3} \beta_b^{IND} X_t^p(\cdot,b,\cdot,\cdot,\cdot) + \sum_{c=2}^{10} \beta_c^{STOCK} X_t^p(\cdot,\cdot,c,\cdot,\cdot) + \\ & + \sum_{d=2}^{3} \beta_d^{VAL} X_t^p(\cdot,\cdot,\cdot,d,\cdot) + \sum_{e=2}^{3} \beta_e^{SIZ} X_t^p(\cdot,\cdot,\cdot,\cdot,e) + \\ & + \sum_{c=2}^{10}\sum_{d=2}^{3} \gamma_{c,d}^{MOMVAL} X_t^p(\cdot,\cdot,c,d,\cdot) + \sum_{c=2}^{10}\sum_{e=2}^{3} \gamma_{c,d}^{MOMSIZ} X_t^p(\cdot,\cdot,c,\cdot,e) + \\ & + \sum_{d=2}^{3}\sum_{e=2}^{3} \gamma_{d,e}^{VALSIZ} X_t^p(\cdot,\cdot,\cdot,d,e) + \eta^p_{t+1}. \end{aligned} \tag{4.9}$$

A Wald-test indicates that cross-effects between country, industry, and individual momentum can be omitted (p-value 0.21), as was the case in the previous section. For expositional purposes, we do not present a table with all estimated coefficients, but capture our main findings in Figure 4.2.

The model with cross-effects implies that the expected return on a stock depends on the specific way value and size effects interact with individual stock momentum. Our analysis shows that value (growth) stocks which are also losers on individual, country, and industry momentum have higher expected returns when they have higher (lower) market capitalisations. Stocks that are winners on the three momentum classifications have higher expected returns when they have small market capitalisations and growth characteristics. These observations are substantially different from the picture that would be created when value and size effects are estimated on an additive basis. An additive approach imposes that the expected excess returns on momentum strategies are the same regardless of the value and size characteristics of the underlying stocks.

In Figure 4.2, the expected excess return on a zero investment strategy is shown, consisting of a long (short) position in stocks from the winner (loser) country, industry, and individual momentum portfolios. This picture suggests that momentum strategies yield the highest expected excess return for small stocks with growth characteristics. The low expected excess return for value stocks, especially those with large market capitalization, is worth noting. Apparently, the momentum effect is less pronounced for these combinations. Our results are consistent with the hypothesis of Hong & Stein (1999), which implies that the momentum effect is stronger for smaller stocks, and the findings of Asness (1997), who concludes that momentum strategies work particularly well for growth stocks. Empirical evidence supporting these results is presented in Rouwenhorst (1998), and Hong et al. (2000), amongst others. Daniel et al. (1998) argue with their behavioral model that stocks that are harder to value (i.e. growth stocks) by investors generate a higher level of overconfidence and hence are more prone to exhibit momentum. Our findings are also consistent with this behavioral theory of investor overconfidence.

In this model with nonlinear effects relating momentum, value, and size the impact from industries and countries is relatively low. This corresponds to the results from our previous analysis without value and size effects. These country and industry effects are equal for each of the value and size combinations, since they are assumed to be additive. The additive expected return from being in the winner industry or country equals 0.22 (t-value 0.72) and 0.24 (t-value 1.17) percent, respectively. The difference between the expected returns on industries and countries has almost disappeared, though a higher t-value for industries remains, indicating less uncertainty about this additional return. The result that value and size effects do not explain medium term return continuation is in accordance with Fama & French (1996) and Jegadeesh & Titman (2001), who claim that the expected return of momentum portfolios cannot be attributed to higher loadings on the value and size factor in the three factor asset pricing model introduced by Fama & French (1993).

In conclusion, the results from this section suggest the importance of incorporating nonlinear effects in the analysis of determining the driving force behind the momentum effect when value and size effects are included. The addition of these latter effects does not alter our conclusion that medium term return continuation is driven by idiosyncratic stock effects. However, concentrating on small and growth stocks seems to further increase the expected return on momentum strategies.

4.6 Conclusion

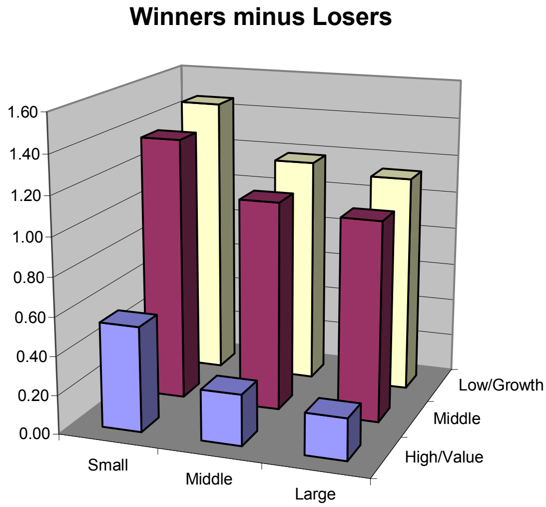
In this chapter, we decompose the expected return on medium term momentum strategies in Europe into country, industry, and individual stock momentum effects using a portfolio-based regression technique, which explains returns on diversified portfolios by evaluating their composition. This method is introduced for several reasons. First, the return on portfolios formed by the traditional way of sorting stocks on the basis of numerous firm characteristics yields many cells with small numbers of observations when the number of characteristics is large. This implies that the estimates are not very precise because they are influenced by idiosyncratic firm effects. Our method is particularly fruitful when there are only a moderate number of stocks in the data set compared to the number of characteristics we want to investigate, since our method requires sorting in one or two dimensions only. Second, a variety of well-understood statistical techniques is available to test model assumptions and hypotheses concerning the driving force behind momentum strategies. Moreover, an intuitively appealing structure imposed upon the model can be tested quite easily.

Our findings indicate that the momentum effect in Europe over the last decennium is primarily driven by an individual momentum effect. The results suggest that economically important (but statistically insignificant) industry momentum effects explain part of the expected return of the momentum strategies. The evidence of a country momentum effect on top of individual and industry momentum is quite weak. Thus, we conclude that the answer to the title is negative; countries and industries do not seem to explain the momentum effect in Europe during the period 1990–2000.

In order to gauge to what extent these results depend on value and size effects, we also incorporate these in our model to decompose the momentum effect. The additive structure to disentangle the momentum effects is rejected and cross-effects between momentum, value, and size appear to be important. The inclusion of these terms marginally influences the results obtained previously. The impact of country momentum is slightly increased, while industry momentum is slightly decreased, resulting in virtually the same additional expected return for both. Thus, our conclusion that country and industry effects do not explain momentum strategies remains unaltered. The decomposition indicates that a European momentum strategy is most profitable for small growth stocks, while large value stocks exhibit least return continuation. These results are consistent with behavioral theories of Hong & Stein (1999) and Daniel et al. (1998).

The analysis presented in this chapter is not only of academic interest. Investment professionals may directly benefit from the decomposition of the momentum effect documented in this chapter. For example, consider an investor with a top-down investment process who first determines the industry and country composition of his portfolio, and subsequently selects stocks within these industries and countries. If the individual momentum effect is subsumed by industry or country effects, information about prior six month returns should be evaluated at the country and industry decision level, while at the stock selection stage further use of past six-month returns would not increase expected returns. Our results indicate that while simultaneously taking into account country and industry momentum effects, there are still return continuations at the individual stock level which might be exploited.

Figure 4.2: **Estimated expected excess returns for European momentum strategy over 1990–2000.** The long side of this portfolio consists of stocks in the winner country, winner industry, and winner individual momentum sort, and the short side of this portfolio consists of stocks in the loser country, loser industry, and loser individual momentum sort. The value and size characteristics of these stocks differ and are displayed in the figure below. The cross-effects between individual momentum and value, individual momentum and size, and value and size effects have been incorporated in the model for the expected returns.



Part II

Asset allocation for pension funds

Chapter 5

The implications of regulatory developments for the asset allocation of pension funds

5.1 Introduction

The regulations concerning the control of financial risks of pension funds has been the subject of debate over the past years. The European Union has proposed to prohibit pension funds of investing in derivatives (including options) or alternative asset classes, such as hedge funds and commodities. The bad stock market climate of the past three years and the related declining solvency of a large number of pension funds has urged the Dutch regulatory body, the Pensions and Insurance Board (Dutch: PVK), to send a letter in which the interpretation of guidelines are clarified to all boards.[1] The PVK announced several measures to restore the solvency of pension funds in the short run. At the same time, a number of requirements on the financial reserves of pension funds are issued. Pension funds that use their own asset liability management (ALM) model must check several specific parameters for compliance with the principles of the PVK.

In the coming years, regulation with regard to the control of financial risks of pension funds will develop as a consequence of at least (a) the transition to the new Pension and Savings Fund Act (Dutch: PSW), (b) the new Financial Assessment Framework (Dutch: FTK), and (c) the introduction of the International Accounting Standards (IAS). Moreover, the imminent merger between the PVK and Dutch Central Bank (Dutch: DNB) could lead to a more directive attitude of the regulator with respect to pension funds and

[1]This letter, dated 30 September 2002, has the subject "Basic assumptions for the financial organisation of pension funds".

many questions need to be answered regarding the harmonization of European pension systems, among which its implications for the control of financial risks.

In this contribution, we aim to list the consequences of the changes in the regulation with respect to the control of several financial risks. In particular, we pay attention to the question in what way the changes in the regulations will affect the asset allocations of pension funds. We argue that the regulatory developments could lead to an asset allocation in which fixed income will again play a bigger role than in the past decade, but in which also alternative assets such as hedge funds, commodities, and inflation-linked bonds have their place.

This paper is organized as follows. In Section 5.2 we provide insight in the consequences of a more market oriented valuation of the (defined benefit) liabilities that follows from recent regulatory developments. Several consequences of the IAS for company pension funds will also be discussed here. In Section 5.3, the possible implications of the regulations involving the solvency and continuity following from the concept draft of the new PSW and the introduction of the new FTK. Section 5.4 discusses the consequences of the regulatory developments with respect to investments in alternative assets. The use of internal models by pension funds is emphasized in the new regulation. Section 5.3 and 5.4 examines the guidelines indicated by the PVK for these models, the monitoring of these internal models, and the question which implications the transition to internal models instead of the standardized models has on the asset allocation. In Section 5.5 we summarize the most important conclusions.

5.2 Market oriented valuation of liabilities

The value of liabilities of pension funds is nowadays still primarily determined actuarially. Expected future liabilities are discounted at the legal maximum allowed annual rate of 4 percent. Since this discount rate is assumed to be constant, the supposed value of the liabilities is insensitive to fluctuations on financial markets. The disadvantage of this approach can be clearly illustrated by considering a pension fund with nominal liabilities and assuming that the actuarial risks are negligibly small. This pension fund is characterized by a fully deterministic future payment scheme. All risks can be hedged by a bond portfolio with the same cash flow pattern.[2] Actuarial valuation of the liabilities combined with market values of the assets, as is common practice nowadays, leads to a reduced funding ratio when for example the interest rate rises, since this is reflected only in lower values for the assets, while the value of the liabilities remains the same. In reality, the change in interest rate has obviously no effect on the perfect match between assets and liabilities.

[2]For simplicity we assume that the actual value of assets and liabilities is exactly the same.

The regulators are also convinced of the limitations of actuarial valuation of liabilities and argue to reach a "consistent valuation, with comparable foundations, of assets and liabilities with the actual value as a starting point".[3] This development coincides with the international development in which, for example in the IAS, market values take a central position. In this section, first the determination of the value of the liabilities in itself is examined, and afterwards the consequences of these changes in the regulation on the level of funding ratios, the fluctuations of the funding ratio, and on the asset allocation of pension funds is described.

The valuation of the liabilities of defined benefit pension schemes using market values is for many reasons no trivial issue. The valuation of nominal liabilities is relatively the easiest. When actuarial risks are neglected, the future expected payments can be discounted using the current term structure of interest rates. Even here the problem arises that the duration of liabilities is usually longer than that of liquid bonds, which implies that the term structure of interest rates has to be extrapolated. Almost all pension schemes have the ambition to index pensions with respect to price or wage inflation. If the term structure for corresponding indexed bonds is available, this can be used to discount the expected fully indexed liabilities. Due to the absence of a market for Dutch inflation indexed bonds, the market value of Dutch liabilities will have to be derived from more or less similar assets that are traded, for example French government bonds linked to the European inflation. This requires advanced valuation methods. When indexation is conditional, for example only when the funding ratio is adequately high, valuation becomes even more complex. For the future it can be expected that pension products with a guaranteed return will be offered, something which is already observed in life insurance products. The determination of market values of these contracts leads to other questions and requires the use of option theory.[4]

Nevertheless, the most essential problem for the determination of actual values of pension liabilities is the nature of the liabilities itself: it concerns almost always incomplete contracts that indicate what is desirable, but leave much freedom for the board of the pension fund, and furthermore it does not commit the board to act a certain way given the occurrence of a scenario. There are no unambiguous ways to value such incomplete contracts.[5] While the transition from actuarial valuation to valuation on the basis of

[3]See, PVK (2001).

[4]See, for example, Hull (2000, Chapter 18).

[5]The PVK recently asked for reactions on several suggestions concerning the valuation of such 'soft liabilities'. In this 'white paper' conditional indexation is, depending on the ambition level of the pension fund, reflected by assuming an indexation probability. Since this valuation technique does not take into account the occasions in which indexation is foregone, this method leads to differences with values obtained when conditional indexation is hard and, for example depending on the solvency, which seems to be undesirable.

Table 5.1: **Conversion coefficient valuation methods.** As an illustration the conversion factor between the current actuarial valuation and the more market-based valuation of the liabilities is calculated for pension obligations with a duration of 20 years.

nominal long rate	expected long inflation	nominal / actuarial	indexed / actuarial
3 %	2 %	1.21	1.78
4 %	2 %	1.00	1.46
5 %	2 %	0.83	1.21
5 %	3 %	0.83	1.46
6 %	2 %	0.68	1.00
7 %	2 %	0.57	0.83

actual values is conceptually a big step forward, it is far from obvious how to determine the actual value adequately, let alone how the regulations and monitoring on the valuation should be designed.

The transition from actuarial values to valuation using actual value has potentially a large impact on the assessment of the funding ratio, and on the deployment of instruments of the pension fund board, such as the choice of asset allocation, the contribution rate, and the choice to cut back on pension schemes.

A first impression of the order of magnitude of the effects on the funding ratio can be found by assuming a pension fund of which the liabilities can be described by one payment on a 20-year horizon.[6] We assume further that the risk premium associated with inflation risk is negligibly small. Under these assumptions it can be verified that the market value of nominal pensions can be obtained by discounting using the nominal long interest rate, while the correct discount rate for a fully inflation indexed pension is the nominal yield minus the expected inflation. The actuarial valuation uses a real discount rate of 4 percent.

The change in valuation methodology can easily lead to a substantial change of the funding ratio, depending on the current interest rate and inflation expectation. If inflation-indexation is not applied, the value of the now nominal liabilities is reduced by 17 percent compared to actuarial methods when the current interest rate is 5 percent. In this case, the funding ratio with market oriented valuation will look brighter than the actuarial variant. In contrast, indexed pensions are increased by 21 percent compared to actuarial methods when the nominal long rate is 5 percent and the expected inflation is 2 percent.[7] For pension funds that currently have a questionable funding ratio this revaluation could lead to solvency problems. See Table 5.1 for revaluation factors for other market circumstances.

[6]The horizon can also be regarded as the weighted average duration of the liabilities. In that case the mentioned interest rate in Table 5.1 symbolizes the weigthed average yield of the entire liability portfolio.

[7]Steenkamp (1998) observes also that the level of funding surplus is highly dependent on the valuation of liabilities.

Table 5.2: **Assumed expected returns on the investments and liabilities in percentage per annum.**

Investments	Expected return	Restrictions of PVK	Standard deviation
Stocks	11.0	≤ 8.0	20.0
Bonds	6.0	≤ 5.0	8.0
Commodities	6.5	–	20.0
Hedge funds	7.5	–	9.0
Liabilities			
Inflation	2.5	≥ 2.0	1.5
Bonds	6.0	≤ 5.0	8.0
Inflation bonds	6.0	–	6.0

Table 5.3: **Assumed correlations between assets and liabilities ($\times$ 100)** Since the average returns, volatilities, and correlations depend on the used benchmark index and sample period our results are an illustration. The chosen values are based on comparisons from the literature and own calculations based on data starting from 1946–2001. Since no inflation-indexed obligations are traded in The Netherlands, we use a model from Bridgewater with simulated returns. The returns of hedge funds are based on Agarwal and Naik (2003) and own calculations with a fund-of-fund index provided by Managed Accounts Reports (MAR).

Correlatie	Stocks	Bonds	Comm.	Hedge	Infl	Infl bonds
Stocks	100					
Bonds	30	100				
Commodities	-20	-20	100			
Hedge funds	50	10	30	100		
Inflation	-30	-10	0	-30	100	
Inflation bonds	0	70	0	0	50	100

Note that the difference between the actuarial discount rate and the nominal yield is of importance for the transformation to nominal schemes, while the difference between the actuarial discount rate and the real rate is key for the revaluation of indexed pension schemes.[8]

From the discussion above it not only becomes clear that the valuation of liabilities using market values is difficult, but that differences in valuation methods may have substantial influence on the answer on the question whether a given pension fund currently has sufficient funding for the liabilities by means of the assets in portfolio, and how adequate funding can be established when necessary. This will be examined in Section 5.3.

[8]Wolff & Ooms (1998) plead for a market-based valuation of the liabilities and remark that the current actuarial real discount rate of 4 percent is substantially above the realized level of 2 percent during the period 1956–1996 in The Netherlands.

Table 5.4: **Relationship between the valuation of liabilities, asset allocation, and expected growth and volatility of the funding ratio.** This table is calculated with expectations, volatilities, and correlations from Tables 5.2 and 5.3. The expected growth and volatility of the funding ratio for different asset allocations using different valuation methods is displayed. The actuarial valuation is performed by using the standard maximum nominal discount rate of 4 percent for nominal obligations, and 4 percent plus expected inflation for real obligations. In order to calculate the market value of nominal and real liabilities, nominal and real bonds are used. The expected growth and volatility are denoted in percentages per year.

Portfolio weights	Expected growth funding ratio			Standard deviation funding ratio		
Bonds/stocks	50/50	75/25	100/0	50/50	75/25	100/0
Valuation Liabilities						
Actuarial (nominal)	4.50	3.25	2.00	11.83	8.89	8.00
Actuarial (real)	2.00	0.75	-0.50	12.35	9.36	8.29
Market (nominal)	2.50	1.25	0.00	9.59	4.80	0.00
Market (real)	2.50	1.25	0.00	11.93	8.04	5.73

The valuation of liabilities will also have an influence on the asset allocation of pension funds. When the liabilities are valued using actuarial methods, the essence of the decision to invest in stocks or bonds is the trade-off between the additional expected return of stocks and the lower risk of a bond portfolio. An extra argument in favor of bonds is introduced when the liabilities are valued using market values: the value of this part of the asset portfolio will comove with the value of the liabilities and hence the risk of fluctuations in the funding ratio are decreased. A numerical illustration can be found in Table 5.4, based on the assumptions about expected returns, standard deviations, and correlations in Tables 5.2 and 5.3. An allocation of 75/25 to bonds and stocks has a risk of 4.8 percent for a nominal portfolio, while the actuarial valuation has a risk of 8.9 percent.

The relevant financial risk for a pension fund is not the fluctuation of the value of the assets itself, but the fluctuations in the funding ratio.[9] Table 5.4 illustrates that nominal market valued liabilities can in principal be matched by a bond portfolio, which results in a riskless pension fund. The price that has to be paid is a zero expected growth in the funding ratio, which results in a higher contribution rate or more austere pension schemes than in case of partly investing in stocks. Table 5.4 also illustrates that the trade-off between risk and return when liabilities are valued using actuarial methods leads to a smaller weight in bonds, because the match with liabilities is not taken into account.

The board of a pension fund will try to prevent large fluctuations in the funding

[9]The funding ratio is only one of the possible indicators to measure the liquidity and solvency of pension funds. See, e.g., Leibowitz, Kogelman & Bader (1994) or Ponds & Quix (2002) for a description of the advantages of using the funding ratio return for analyzing pension fund solvency.

ratio, because these may lead to unwanted fluctuations in for example the contribution rate. Nominal and real obligations are therefore, as argued above, extra attractive when valuation using market values are brought into force. Company pension funds also have other developments in mind. As soon as the IAS are brought into force, the company is required to report the results of its pension funds on the profit and loss account to a large extent.[10] The fluctuations in the value of pension funds are of such magnitude that they can substantially influence the annual profit and loss account. Undoubtedly, this development in the regulation will lead to additional pressure from the parent company to the pension fund to avoid large fluctuations in the funding ratio, and hence invest particularly in fixed income securities.

5.3 Assessing solvency and continuity

Until recently the funding ratio was used by the regulatory bodies as a tool to investigate the financial health of a pension fund and determine whether it is likely that the fund will meet its obligations in the future. The PVK has acknowledged that it considers these valuation methods as "not sufficiently dynamic" and furthermore that they "put too much emphasis on the current situation".[11] Besides the discussed struggle with the question how the value of the liabilities, and hence the funding ratio, can be determined best, it is pointed out that the contributions are used only after many years for the pension payments. Several Dutch pension funds have emphasized that also in case of underfunding (that is, a funding ratio below one), the "payment security" can be high, because received contributions alone will be enough for the coming decade to meet the pension liabilities.[12] The continuity principle on which these statements are based emphasizes that, special circumstances left aside, nobody can directly claim the assets and liabilities of pension funds and in this way redeem the assets for a certain group of people and leave others penniless. In this view a situation of underfunding is only a problem if the continuity of the parent company is broken, for example through bankruptcy, or when people are evading the company or industry because of the prospective high pension burden.

The funding ratio still plays an important role in the foundations of the new FTK, which will serve as a basis for new pension fund regulation, but these are supplemented by so called solvency and continuity assessments. The horizon for a solvency assessment is one year, and it should be indicated how the current investment, contribution, and

[10] The regulation allows certain smoothing when the funding ratio of the pension fund is close to one. For simplicity we do not take this into account in our analysis.

[11] See PVK (2001).

[12] Other pension funds have emphasized the importance of a sufficient funding ratio, because otherwise expenses will be shifted to future generations and the capital funding system changes to a pay-as-you-go system.

indexation policy would be able to absorb unfavorable external developments, such as adverse investment returns. The continuity assessment deals with longer horizons and investigates how policy changes can be used to meet unfavorable scenarios.

An important difference between the determination of the funding ratio on the one hand, and the continuity or solvency assessment on the other hand, is that the funding ratio can, at least in principle, be determined on the basis of observed variables.[13] For this number a hard lower bound can be prescribed. The future funding ratio assuming certain pension fund policy, on which the continuity and solvency assessments are based, is a stochastic quantity of which only the distribution can be described by the use of so-called ALM models. For these assessments, it is impossible to require a certain amount of funding. The regulator can at most prescribe that the probability to arrive below a certain level should be smaller than a certain percentage. Moreover, implementation of both tests requires assumptions on the possible future paths of a variety of financial returns and inflation, which cannot be derived from observed market prices. Adequate implementation of the continuity and solvency assessment requires competent supervision on the principles underlying the used ALM models.

Both the current funding ratio and the path towards sufficient financial buffers in the future play a prominent role in the letter that the PVK sent to the boards of pension funds in September 2002 in consequence of the adverse developments at the stock exchanges. In case of underfunding, the fund is required to present a plan indicating how underfunding will have disappeared within a one year horizon. The distribution of the future funding ration can be determined by assuming a certain investment policy and future pension contributions, combined with a decision about inflation-indexation of the pensions. In Table 5.5 the results of a simplified ALM model are displayed. We assume an unchanged premium policy, full indexation of the liabilities, an asset allocation of 50 percent in (nominal) bonds and 50 percent in stocks. For simplicity, we assume that the (log)returns on stocks and bonds, but also inflation are independently and identically normally distributed with parameters as described in Table 5.2 and 5.3.[14] The real liabilities are valued using market based valuations, as in the previous section. Table 5.5 contains the results for a pension fund with initial funding ratio equal to 110.[15]

Given the model assumptions, the second and third column of Table 5.5 indicate that

[13] We note that from a practical perspective determining the funding ratio is far from trivial and can only partially be based on observed prices; see also Section 5.2.

[14] This illustration can be made more realistic straightforwardly, by for example modeling inflation according to an autoregressive model.

[15] Given the assumptions, it holds that the funding ratio (FR) on a horizon of one year is $FR_{t+1} = FR_t + FR_t \cdot (wr_{s,t+1} + (1-w)r_{nb,t+1} - r_{rb.t+1})$, where the return on the funding ratio is approximated by the difference between the return on assets and liabilities. The weight to stocks is denoted by w, the returns by r, where s refers to stocks, nb to nominal bonds, and rb to real bonds. The probabilities follow from this formula.

Table 5.5: **Distribution future funding ratio.** We assume an initial funding ratio of 110 and real, market-based liability valuation. The investment horizon is one to five years, and asset allocations of 50/50 and 75/25 in bonds/stocks. In addition to the expected funding ratio, also the probabilities of the funding ratio falling below a certain level are displayed.

Allocation (bonds/stocks)	50/50		75/25	
Horizon	one year	five years	one year	five years
Expected return on the funding ratio, per year	2.50 %		1.25 %	
Standard deviation on the funding ratio, per year	11.9 %		8.0 %	
Expected funding ratio	112.8	123.6	111.4	117.0
Pr{funding ratio < 80}	0.01	0.09	0.00	0.04
Pr{funding ratio < 90}	0.04	0.15	0.01	0.10
Pr{funding ratio < 100}	0.17	0.23	0.10	0.21
Pr{funding ratio < 110}	0.42	0.33	0.44	0.37
Pr{funding ratio < 120}	0.71	0.45	0.84	0.56
Pr{funding ratio < 130}	0.91	0.57	0.98	0.73
Pr{funding ratio < 140}	0.98	0.68	1.00	0.86
Pr{funding ratio < 150}	1.00	0.78	1.00	0.94

the expected funding ratio in one year is slightly higher than the current funding ratio, the probability of a funding ratio below the crucial level of 100 in one year is 17 percent, and below 100 in five years is 23 percent. The probability of a funding ratio below 90 in one year is in this example 4 percent. In a white paper, the PVK announced in March 2003 that financial buffers should be such that the probability of underfunding on a one-year horizon should be less than 0.5 percent.[16]

An important question we pose is whether the new regulation will lead to an increased or decreased weight of stocks in the optimal asset allocation of pension funds. The fourth and fifth column describe the distribution of the funding ratio if only 25 percent is invested in stocks. Evidently, this leads to a lower expected return, but also a lower volatility of the funding ratio. If in the new solvency assessment of the FTK the focal point would be on the expected funding ratio, the new regulation would lead to an incentive to increase the weight of stocks in the allocation. However, the note about the basic principles underlying the FTK seems to emphasize "an unfavorable scenario within a year", which suggests that the solvency assessment is primarily designed to examine the probability of underfunding. From Table 5.5 follows that the probability of underfunding in one year decreases if the volatility of the asset allocation (relative to the liabilities) is decreased. Thus, this change

[16]In addition to the two white papers mentioned before, the PVK is planning to publish a third white paper in the summer of 2003 with its views on the implementation of the continuity test.

in the regulation will also, like the change to market-based valuations of pension fund liabilities described in Section 5.2, lead to a reduction of the weight of stocks in the allocation of pension funds.

In the above we assumed that the simplified ALM model of our illustration would be labeled adequate by the regulator, and we have disregarded the required financial buffers.[17] These issues will be discussed below.

The announcement of the PVK to the boards of pension funds suggests that in principle only ALM models will be approved if the used parameters are in accordance with several conditions. Specifically, the expected return on fixed income securities is not allowed to exceed 5 percent, the expected return on equities is not allowed to exceed 8 percent, an the expected price and wage inflation are at least 2 and 3 percent, respectively.[18] Without doubt the goal of these restrictions is that pension funds do not base their investment policy and contribution rates on too optimistic ALM analyses. The consequences of these restrictions are substantial. Note that the restrictions on expected inflation are not binding in our example. Table 5.6 is similar to Table 5.5, but the expected returns on equity and bonds, which were outside the allowed range, have been put at the maximum allowed values. Since the restricted expected return on stocks is far lower than the historic average over a long sample period that is used in many ALM studies, this regulatory adjustment will cause a lower weight in stocks than presently common when the unfavorable probabilities are of concern. It also follows from Table 5.6 that the costs in terms of the reduction in the expected return on the funding ratio are substantial, with an expected increase of only 0.75 percent per annum for the 75/25 allocation.

As mentioned before, the letter of the PVK also contains rules about the required financial buffers that pension funds should possess. The fund should be able to sustain a drop of 40 percent in the stock market with respect to peak in the last 48 months. The fund should also be able to sustain a drop of 10 percent in the stock market with respect to the peak in the last 12 months. Allocations to fixed income securities are subject to different regulations, when the interest rate is 4 percent, the buffer should be 10 percent

[17] Pension funds may also choose to base their risk budgetting on standardized models as an alternative for the use of internal models. In such standardized model, the regulator prescribes several unfavorable scenarios. It is as of yet unclear which valuation method is used for the assets and liabilities in, e.g., in the scenario of declining interest rates. The increase in liability values as a consequence of declining interest rates does not seem to be easy in standardized models that do not make use of liability valuation methods, which is not desired in such standardized models. If the valuation of assets deviates too much of that of liabilities, the incentive to invest in fixed income is reduced because the absence of the natural hedge between bonds and liabilities.

[18] Fama & French (2002) estimate the future risk premium on equity for the US market between 2.55 and 4.32 percent. They explain the difference between historical and future expected stock returns by a decreased discount rate, which has increased stock prices over the past decades. They do not expect the discount rate to reduce further in the future. Note that the restriction by the PVK is formulated in terms of a maximum 3 percent equity risk premium, so pension funds cannot lower the expected returns on bonds below 5 percent without lowering the expected return on equities further.

Table 5.6: **Distribution future funding ratio.** We assume an initial funding ratio of 110 and real, market-based liability valuation. The investment horizon is one to five years, and asset allocations of 50/50 and 75/25 in bonds/stocks. In addition to the expected funding ratio, also the probabilities of the funding ratio falling below a certain level are displayed. The return on stocks and bonds has been set to the maximum allowed values of the PVK of 8 and 5 percent, respectively.

Allocation (bonds/stocks)	50/50		75/25	
Horizon	one year	five years	one year	five years
Expected return on the funding ratio, per year	1.50 %		0.75 %	
Standard deviation on the funding ratio, per year	11.9 %		8.0 %	
Expected funding ratio	111.6	118.4	110.8	114.2
Pr{funding ratio $<$ 80}	0.01	0.11	0.00	0.05
Pr{funding ratio $<$ 90}	0.05	0.18	0.01	0.12
Pr{funding ratio $<$ 100}	0.19	0.28	0.11	0.24
Pr{funding ratio $<$ 110}	0.45	0.39	0.46	0.42
Pr{funding ratio $<$ 120}	0.74	0.52	0.85	0.61
Pr{funding ratio $<$ 130}	0.92	0.64	0.99	0.78
Pr{funding ratio $<$ 140}	0.98	0.75	1.00	0.90
Pr{funding ratio $<$ 150}	1.00	0.84	1.00	0.96

of the value of fixed income securities, and at a rate of 5 percent the buffer should be 5 percent of the value of fixed income securities. At an interest rate of 6 percent or higher the fund does not require a financial buffer.

This regulation will also influence the optimal asset allocation of pension funds. For example, since all fixed income securities are considered equally risky, pension funds get the incentive to invest more in bonds with higher expected return, but also higher default risk. Here, we limit ourselves to the allocation between government bonds and equities. Assuming that the stock market today is below the 40 percent and 10 percent of the four and one year peaks respectively, and a current interest rate of 6 percent, the fund in our example is required to have a funding rate of 105 when the weights to stocks and bonds are both 50 percent, and 102.5 if only 25 percent is invested in stocks. In this example, the probability of staying over the required limit in the next year is larger in case of a smaller weight to equities. Again, this regulation leads to a reduction in the weight of stocks in the optimal asset allocation. Note, however, that this is not always the case. If the interest rate in the previous example is 4 percent, the required funding ratio is 110, no matter how much is invested in stocks or bonds. The probability that this target level is not met within one year is slightly higher (about 46 percent) with the more defensive asset allocation.

5.4 Restricted investment opportunities

Nowadays, restrictions on the investment opportunities for pension funds exist in many European countries; see e.g. Legge (2002). Some countries have a maximum weight on equity allocations (e.g. France, Denmark, and Austria), while in other countries only part of the assets can be invested internationally (e.g. Germany). The differences in regulation are particularly large for the possibility of pension funds to trade derivative securities or invest in alternative investments such as commodities, hedge funds, and private equity. Alternative investments are increasingly popular with institutional investors. In the US the total market value of this category in the portfolio of institutional investors has increased from \$ 10 billion to \$ 232 billion over the period 1986-2001. Europe has seen a growth in alternatives from 1.6 percent of total assets to 3.6 percent in a period of 5 years.[19]

The arguments in favor of restrictions on the investment opportunities are based on the impression that the investment risks would increase as alternatives are added to the pension fund portfolio. Having the presidency of the EU in the spring of 2002, Spain tried to launch new pension fund regulations prohibiting the use of derivatives and alternative investments. Obviously, the unprofessional use of derivatives or investments in unknown investment objects could lead to possibly unacceptable risks. One of the core theories of finance is that diversification over more assets or asset categories only reduces the risk relative to a situation in which investments are restricted, provided that investment management is professional. Consequently, it is to be expected that as pension fund boards in European countries get more professional, the restrictions on the investment categories will disappear.[20]

In this section we investigate how attractive alternative asset classes such as commodities and hedge funds are for pension funds and how the answer to this question is related to the valuation method of the liabilities. For an asset-only analysis of the importance of hedge funds in the institutional portfolio, see e.g. Gregoriou & Rouah (2002) or De Ruiter (2001). Note, however, that not just the risk and return characteristics of asset classes play a role, but also the relation with inflation, and in case of market-based valuation, the relation between the returns on alternatives and the change in interest rates. We also aim to examine the changes in optimal asset allocation after a possible change in the regulation in this direction.

Often, commodities have a positive return when stock markets perform poorly. In this view, commodities protect a portfolio when revenues from other investment classes are

[19]Source: *Alternative Investing by Tax-Exempt Organisations 2001*, Goldman, Sachs, and Co. and Frank Russell Company.

[20]See also Frijns, Maatman & Steenkamp (2002).

disappointing.[21] Moreover, there is a positive relation between an increase in commodity prices and consumer prices. Hence, investments in commodities for pension funds with inflation-indexed obligations are particularly attractive. Chapter 6 of this thesis and Froot (1995) confirm the advantages of investing in commodities from the perspective of a US pension fund. In this section we investigate the advantages of investing in commodities for a Dutch pension fund.

The correlation between commodities and traditional asset classes is negative. In contrast to the US, where the correlation between inflation-indexed liabilities and commodities is positive, there seems to be a slightly negative relation for the Dutch market if we use the Goldman Sachs Commodity Index (GSCI) and the simulated Bridgewater Dutch inflation-linked bond returns over the period 1971-2001.[22]

Another alternative asset class is hedge funds, which is claimed to be (at least partially) market neutral and hence may lead to huge diversification benefits without reducing the expected return on the portfolio. Since historic return data on this category are based on voluntarily reporting and less successful hedge funds disappear quickly, numerous biases in hedge fund data sets have been reported.[23] Agarwal & Naik (2003) unravel the investment behavior of hedge funds with the use of style analysis. For more on style analysis, see Chapter 7 of this thesis. They use the results of this style analysis to calculate average returns corrected for the fact that real data is only available for a short period of time with mostly high stock returns. Their estimation for the expected return on fund-of-fund hedge funds, which are most relevant for European institutional investors, is about 7.5 percent per annum. Their analysis also indicates that the unconditional volatility of hedge funds is larger than what we have seen over the past decade. These adjusted values have been used in the remainder of this section. The correlation between hedge funds and Dutch inflation is of about equal size as equities and inflation, –0.30. The correlation of hedge funds with commodities is positive, based on the fund-of-fund hedge fund index of Managed Accounts Reports (MAR). The correlation between Dutch inflation-linked bonds and hedge funds is almost zero.

For convenience, we assume a stylized example in the remainder of this paper. In Table 5.2 and 5.3 we display the expected returns, volatilities, and correlations of the investment classes, extended with commodities and hedge funds. As of yet, it is unclear whether the PVK intends to prescribe maximum values for expected returns on alternative asset classes for ALM studies. Obviously, these parameters are of importance for estimation of

[21] During the period January 2000 and December 2002 commodities (measured by the GSCI) had an average return of 11.5 percent per year, while a global stock portfolio returned –13.6 percent annually. See also Chow, Jacquier, Kritzman & Lowry (1999) for diversification benefits of commodities in periods of negative returns on stock markets.

[22] See for more information `www.gs.com/gsci` and `www.bwater.com/research_ibonds.htm`.

[23] A detailed discussion about biases in the available data on hedge funds is, e.g., Fung & Hsieh (2000).

the risks of the investments. For the answer on the question whether it is relevant to invest in commodities and what the risk reduction of this addition would be it is not sufficient to specify the expected returns meaningful. Also volatilities, correlations between returns and inflation and the autocorrelation-structure of inflation play a role when estimating the risks of a pension fund with liabilities that are market-based. However, it seems unlikely that the regulator will prescribe an interval for these parameters.[24]

Firstly, we analyze the diversification benefits of both alternative assets for a pension fund that values its liabilities according to the current PVK norms of 4 percent plus inflation. Secondly, we analyze the effects of a market-based valuation of the liabilities, as discussed in Section 5.2.

The optimal allocation for a pension fund that is not allowed to invest in the aforementioned alternative assets by the regulator consists of 50 percent in bonds and 50 percent in stocks with an expected return on the funding ratio of 2 percent per annum. The volatility on the funding ratio is 12.4 percent. If we do not restrict the pension fund, the risk of the fund can be reduced to 10.4 percent. The weights in commodities and hedge funds are 15 and 33 percent, respectively. Investments in the traditional asset class bonds are reduced substantially, as can be seen from Table 5.7. If the PVK restrictions on the expected return on bonds and stocks are taken into consideration, the weight in alternative asset is obviously increased, while stocks are not in the optimal asset allocation. This is not surprising, since hedge funds now have about the same expected returns as stocks, but a substantially lower variance. At this moment, it is unclear how the PVK will regulate alternative investments at pension funds. While for other reasons it might not be optimal for the pension fund to invest in the alternative assets with the weights resulting from this analysis, our illustrative example indicates that alternatives might provide additional diversification benefits, and a too stringent European regulation might prevent possible risk reductions.

As mentioned before, the correlation between returns on alternative assets and pension fund obligations is also important when liabilities are valued market-based. The optimal allocation for a pension fund with market-based liability values, which is restricted by the regulator to invest only in bonds and stocks, is 50 percent bonds and 50 percent stocks, given an expected return on the funding ratio of 2.5 percent. The volatility is in such case equal to 10.4 percent, as can be seen in Table 5.7. The alternative investments that we discuss in this paper show no positive correlation with Dutch inflation-indexed obligations. Nevertheless, the new optimal allocation consists of 25 percent in alternatives,

[24] An important question remains how the supervision on these models should be organized. To us it seems desirable that each pension fund publishes a publicly available document with the specification and features of the ALM-model. This way, others besides the PVK may also judge the models on their merits.

Table 5.7: **Alternative assets in the strategic allocation.** In this table the weights of the various assets in the optimal pension fund portfolio with real obligations are displayed. The columns 'actuarial' and 'market-based' indicate the method of liability valuation. In the right side of the table the restrictions on the expected returns of stocks and bonds of 8 and 5 percent, respectively, are displayed.

	Without PVK restrictions				With PVK restrictions			
	Actuarial		Market-based		Actuarial		Market-based	
	Trad.	Alt.	Trad.	Alt.	Trad.	Alt.	Trad.	Alt.
Expected return	2.0 %	2.0 %	2.5 %	2.5 %	0.0 %	0.0 %	1.5 %	1.5 %
Standard deviation	12.4 %	10.4 %	10.3 %	9.2 %	12.4 %	7.0 %	11.9 %	7.4 %
Bonds	50 %	25 %	50 %	29 %	50 %	37 %	50 %	39 %
Stocks	50 %	46 %	50 %	45 %	50 %	- 4 %	50 %	-3 %
Commodities	–	15 %	–	15 %	–	5 %	–	1 %
Hedge funds	–	33 %	–	10 %	–	62 %	–	62 %

divided between 15 percent commodities and 10 percent hedge funds. The volatility on the funding ratio is reduced to 9.2 percent, keeping the expected return on the funding ratio constant. While hedge funds and commodities already form a substantial part of the pension fund portfolio, an alternative asset with positive correlation with the obligations could reduce the risk on the funding ratio even further. Similarly to the case with actuarial valuation of the liabilities, the exclusion of alternative assets increases the risk on the funding ratio. A more diversified investment portfolio, provided it is prudent, seems to be preferred over a too strict approach.

We note that in principle indexed bonds could eliminate the risk of a pension fund completely because of its hedging properties, but this might mean higher costs for the pension system as a whole. If for Dutch pension funds bonds with similar characteristics as the pension fund obligations would become available, the volatility of the funding ratio could be reduced even further. However, these products are currently only scarcely available.[25]

5.5 Conclusions

In this paper, we have analyzed the consequences of the developments in the regulation for the optimal asset allocation of pension funds. Many developments consist of incentives for pension funds to reduce the exposure to stock markets. This holds, e.g., for the valuation of liabilities according to market values, exposing the hedge between fixed income securities and liabilities, for the regulation of the International Accounting Standards

[25]See, e.g., Boender, Kramer, Steehouwer & Steenkamp (2001), Van der Hoek & Kocken (2002), and De Jong (2003) for a description of the potential benefits of index linked bonds in a pension fund portfolio.

exposing pension profits and losses on the balance sheet of the companies, but also for the prescription of parameters in the ALM models and the rules prescribing that with high certainty the continuity and solvency of the pension funds should be guaranteed.

The return on stocks is higher than the return on bonds on the long run. The incentives in the regulation reducing the weight of stocks in the allocation might lead to rising pension contributions and or reduction of the pension benefits. Partially, these changes are inevitable to restore the confidence in our pension system. The investment risks can be reduced somewhat by portfolio allocations to derivatives and investing in new asset classes such as commodities and hedge funds. While no huge influence on the reduction of the probability of underfunding can be expected of such alternative investment objects, restricting the investment opportunity set as is proposed in Europe could be counter productive when pension funds are governed by professionals and the supervision on the investment behavior of pension funds is adequately organized.

Chapter 6

Strategic and tactical allocation to commodities for retirement savings schemes

6.1 Introduction

Institutions such as insurance companies and pension funds are investigating the benefits of investing part of their wealth in alternative asset classes. Recently, investments in commodities, inflation-indexed bonds, and hedge funds have become increasingly popular. Especially the trade-off between risk and return in these relatively unknown asset classes and the portfolio implications of investing part of their wealth in these asset classes are not yet fully explored. This paper aims to shed further light on the benefits of investing in commodities for investors with a liability structure sensitive to the nominal or real interest rate and inflation.

The interest in commodity investments for institutions dates at least back to Bodie (1980), who points out the potential benefits of commodities for pension funds. In the following years, several papers have confirmed the risk reducing characteristics of commodities. Froot (1995) suggests that commodities are better diversifiers than, for example, real estate and stocks of commodity-related companies. Chow et al. (1999) indicate that commodities can be particularly valuable in adverse economic circumstances, when other alternatives tend to correlate more with traditional assets. These studies focus on nominal asset returns only and find that the benefits of investing in (derivatives on) commodities are most pronounced for investors with high risk aversion. For many investors the optimal portfolio is determined by a trade-off between expected return and volatility of the surplus of assets minus liabilities rather than by the distribution of asset returns only. Individuals or institutions that anage a defined contribution pension scheme will often be primarily concerned with the surplus of the asset value over the discounted value of expected future payments in real terms. They will therefore take interest and inflation risks in the liabilities into account when selecting their asset portfolio. This is a fortiori true for defined benefit schemes. Individuals or institutions with nominal future liabilities will take the interest risk involved into account. Commodities might be particularly suitable for pension savings because of their positive relation with inflation.

The first contribution of this paper is our examination of the benefits of investing in commodities for investors with financial liabilities. We treat these financial liabilities as fixed, because there is in general no liquid market to trade these pension claims. The terminology 'fixed' indicates that we assume that desired annual future cash flow is predetermined, not that the value of the liabilities does not change over time. This is an extension of the asset-only approach, which is used in the existing literature. Incorporating correlations between the returns on assets and liabilities may lead to substantially different portfolio weights in an optimal asset allocation than in the traditional asset-only approach. We consider two types of pension schemes, one with liabilities in nominal terms, and one with liabilities in real terms (i.e. protected against inflation).

Our second contribution is that in addition to the existing evidence on the *economic* significance of adding commodities to an existing portfolio of stocks and bonds, we also provide evidence on the *statistical* significance of the outward shift of the mean-variance frontier. Although Bodie (1980) and Froot (1995) provide empirical evidence on the benefits of commodities as alternative investments, a statistical analysis on the importance of the shift of the mean-variance frontier is not included. These tests for significant improvements are based on regression analysis; see, e.g., Huberman & Kandel (1987).

Finally, we contribute by investigating multiple investment horizons. We distinguish asset allocation for a long-term strategic (three-year), and short-term myopic and tactical (three-month) horizon.[1] For the short-term cases we investigate whether commodities expand the three-month buy-and-hold frontier, but also whether these short-term deviations expand the strategic buy-and-hold frontier. Since there is some evidence that expected returns and covariances change over time, we examine both unconditional and conditional spanning of commodities by the traditional asset classes. Whereas tests for unconditional spanning indicate whether commodities expand the mean-variance frontier without using information about the current economic state, conditional spanning tests answer whether the frontier shifts given the economic state we are currently in. We also aim to answer whether quarterly tactical timing strategies between commodities and stocks further reduce the variance risk of efficient strategic portfolios.

[1] We are aware that strategic might refer to many, possibly longer, investment horizons than used in the paper. However, longer horizons are rarely used for buy-and-hold strategies. Note that we consider a one-period model, and hence the three-year horizon is in some sense also myopic.

The current discussion among regulators in the European Community concentrates on introducing/relaxing restrictions on the asset side, as well as finding a “fair value” for pension claims on the liability side. A lively debate was triggered by the Spanish government proposing restrictions on investments in alternative asset classes and derivatives by pension funds. The decision has been taken that pension funds that operate in across country borders in the European Community are severely restricted in their use of derivatives and investments in alternatives.[2] In this light, our paper aims at answering whether alternative asset classes such as commodities might reduce overall risk, and hence we investigate whether introducing restrictions for these asset classes are more likely to harm then protect the fund’s participants.

Our results indicate that there is a substantial difference in the optimal asset allocation for a pension scheme with nominal liabilities compared to a scheme that compensates its beneficiaries with inflation. Within the framework analyzed here, a pension scheme with nominal liabilities that already optimally invests in long-term government bonds, domestic stocks, and foreign stocks, cannot significantly improve the trade-off between expected return and volatility of the portfolio by investing in commodities. In contrast to pension schemes with nominal liabilities, pension schemes with real liabilities can significantly (both economically and statistically) improve the strategic risk-return trade-off by investing part of their wealth in commodities. This is due to the inflation-hedge provided by commodity investments.

In the quarterly myopic setting, when information about the economic situation is ignored, the spanning hypothesis is not rejected for the nominal scheme, but is rejected for the inflation-indexed scheme. This result was also obtained from the strategic spanning tests. However, when we use conditional information about the bond yield, term spread, default spread, and inflation, it turns out that commodities can shift the mean-variance frontier significantly outward for pension schemes with nominal liabilities. Thus, even when from a strategic perspective commodity returns are spanned by the traditional assets, at a quarterly horizon they might provide additional diversification benefits using dynamic strategies. Tactical timing strategies between commodities and stocks may shift the strategic frontier even further outward, suggesting that active short-term investment strategies can reduce the long-term portfolio risk even further.

The remainder of this paper is organized as follows. In Section 6.2, we investigate the strategic mean-variance efficient (MVE) frontier for a pension scheme with fixed liabilities (in real or nominal terms). In particular, we examine whether a strategic allocation to commodities expands the MVE frontier. In Section 6.3, we examine the optimal asset

[2]See for example ‘Spain to put the clock back’ (*Investments and Pensions Europe*, March 2002, p. 2) and Legge (2002) for comments on the recent proposal of pension reforms in the European community.

allocation for a myopic investor with a quarterly investment horizon. We analyze unconditional spanning and moreover allow the use of macro economic information to determine the optimal expected risk-return trade-off. In this section we also aim to answer whether tactical timing strategies between commodities and stocks expand the MVE frontier of strategic buy-and-hold portfolios even further. In Section 6.4 we perform some robustness analyses. Finally, Section 6.5 concludes.

6.2 Strategic asset allocation

The portfolio problem of investors in pension schemes is defined in return on assets *relative* to return on liabilities rather than the usual asset-only approach. For a defined benefit pension scheme the volatility of the *return on assets relative to liabilities* is of concern rather than the asset returns themselves. Thus, high volatility in asset returns is not necessarily perceived as risky by these investors, because the correlation of assets with liability returns determines the volatility of the net position of the scheme.

We assume that the investor has a mean-variance utility function in the return on the funding ratio, i.e.,

$$U(R_t^{FR}) = \mathrm{E}\{R_t^{FR}\} - \gamma \mathrm{Var}\{R_t^{FR}\}, \tag{6.1}$$

where U denotes the utility function, γ the investor's risk aversion, and R_t^{FR} the return on the funding ratio. The funding ratio is defined as the value of assets devided by the discounted value of liabilities. The return on the funding ratio is defined as the difference between the return on the assets and liabilities,

$$R_t^{FR} = R_t^A - R_t^L, \tag{6.2}$$

where R_t^A, and R_t^L are the return on the assets and liabilities.[3] When the investor has no liabilities, the problem reduces to the usual mean-variance optimization problem. This approach also fits with the full surplus maximization for a pension fund with funding ratio equal to one, as indicated by Sharpe & Tint (1990).[4] Since we analyze a pension scheme with utility derived from the mean and variance on the funding ratio instead of the surplus, our approach does not depend on the initial funding ratio; see, e.g., Leibowitz

[3]This is due to log-approximation of the definition of the return on the funding ratio (FR_t),

$$\ln\{1 + R_1^{FR}\} = \ln\{FR_1\} - \ln\{FR_0\} = R_1^A - R_1^L$$

[4]In their setup, the surplus is defined as $S_t(k) = A_t - k \cdot L_t$, with k the 'importance' of liabilities, with $k = 1$ for a full surplus optimization. Dividing the surplus at the end of next period by the current value of the assets yields shows that suplus maximization is equal to maximization of $R_t^A - k \cdot FR_0^{-1} \cdot R_t^L$. Our funding ratio return is the same as surplus maximization when $k = FR_0$.

et al. (1994). The optimal portfolio weights can straightforwardly be derived to equal

$$w^{opt} = \gamma^{-1}\Sigma_{RR}^{-1}(\mu_R - \eta\iota) - \Sigma_{RR}{}^{-1}\Sigma_{RL}\mu_L, \tag{6.3}$$

where μ_R and μ_L are the expected return on the assets and liabilities, Σ_{RR}, is the variance matrix of asset returns, and Σ_{RL} the covariance between assets and liabilities. Note that η is known as the the zero-beta rate, and is a function of γ.[5] The first term of this expression is the asset-only optimal portfolio. The second term in equation (6.3) accounts for the covariance between the returns on the assets and liabilities. Obviously, if these returns are uncorrelated, the optimal portfolio does not change. A positive correlation between the asset and the liabilities leads to an increase of the weight of this asset in the optimal portfolio, since it decreases the volatility of the funding ratio.

We examine two types of pension schemes in the analyses below. First, we consider a pension scheme that pays nominal pensions to its beneficiaries. The second scheme is committed to pay real (or inflation-indexed) pensions. The value of pension liabilities is not always easy to determine, since there is frequently no liquid market in which these claims are traded. This holds especially for price- or wage-inflation indexed liabilities; see, e.g., Head et al. (2000). For simplicity, this fact is ignored in this paper, and funding ratios are determined using market based valuation of liabilities as if they are fully liquid. The valuation concepts are described in more detail below.

In our first stylized pension scheme, the claims are in *nominal* terms. The return on the (marked-to-market nominal) liabilities is primarily driven by the changes in the yield of bonds. The liabilities can be viewed as a portfolio of nominal bonds and hence appropriate valuation techniques from this line of literature can be used to obtain a "fair" or market value.[6]

The duration of the portfolio of nominal bonds depends on the characteristics (such as age) of the beneficiaries of the pension scheme. We analyze schemes as if the there is one claim that has to be paid 10 years from now.[7] The value of the liabilities for pension schemes with a high duration is sensitive to changes in the nominal interest rate. The return on the nominal liabilities is[8]

$$RNOM_t^L = y_t^{(DUR-1)} - DUR \cdot \left(y_t^{(DUR-1)} - y_{t-1}^{(DUR)}\right), \tag{6.4}$$

where DUR is fixed over time (in our example equal to 10 years), and y_t the nominal yield

[5] There is a one-to-one relation between the zero-beta rate η and the risk aversion parameter γ, $\gamma = \mu'\Sigma^{-1}\iota - \iota'\Sigma^{-1}\iota \cdot \eta$. In this notation, μ is the expected return, and Σ the variance matrix of the returns. The elements of vector ι are all equal to one.

[6] In this paper we use government bond yields to value the liabilities of pension schemes.

[7] This maturity can also be interpreted as the average duration of the total portfolio of claims.

[8] See, for example, Campbell, Lo & MacKinlay (1997), p. 398.

at the end of period t.

The second example considers a pension scheme with future claims in *real* terms rather than nominal terms as in the previous example. This is more rational from an economic perspective and in line with the actual practice in Europe in the last decades, although the indexation of pension claims is much debated recently since the substantial worldwide drop in stock prices in the beginning of this decade. The payment of real benefits complicates the computation of fair values for the liabilities, since this means that future claims should be discounted with the *real* yield instead of the *nominal* yield. Since the US started issuing index-linked bonds only in 1997, historical data about the real yield is not directly available for our empirical analysis. However, Bridgewater has modeled the historical expected inflation and hence have come up with estimated yields of index-linked bonds as if they have been traded from 1970.[9] The value of the liabilities can be regarded as an index-linked bond, and the valuation methods for these assets can be used to determine the value of the liabilities. We again assume that the value of the liabilities is only affected by the real yield. Note that we assume that the inflation risk premium is zero. The return on the liabilities is now

$$\widetilde{R}_t^L = \widetilde{y}_t^{(DUR-1)} - \widetilde{DUR} \cdot \left(\widetilde{y}_t^{(DUR-1)} - \widetilde{y}_{t-1}^{(DUR)} \right), \tag{6.5}$$

where $\widetilde{\cdot}$ refers to real variables rather than nominal ones. For the duration of the portfolio of liabilities we again use 10 years. The nominal return on the real liabilities is the real return plus the realized inflation. Thus,

$$RREAL_t^L = \widetilde{R}_t^L + \pi_t, \tag{6.6}$$

where π_t is the annual inflation rate. Thus, assets that reduce the risk of the portfolio should either be positively correlated with inflation, the real interest rate, or changes in the real interest rate. For portfolios with long durations, the latter component is the most relevant when real yields are changing substantially.

In the remainder of this section we analyze whether it is optimal for the two stylized pension schemes to add commodities to its strategic asset allocation consisting of domestic government bonds, domestic stocks, and international stocks. The strategic investment horizon we investigate is three years. During this period we do not rebalance the portfolio to maintain the initial weights, but analyze a buy-and-hold portfolio instead. This assumption is relaxed when investigating tactical timing strategies in Section 6.4.[10]

[9] See also `http://www.bwater.com/research_ibonds.htm`.

[10] See Campbell & Viceira (2002) for long-term investors who quarterly rebalance their strategic portfolios.

Table 6.1: **Descriptive statistics of assets and liability returns**. In Panel A, the tri-annual log returns (in US dollars) over the sample 1972:12 - 2001:12 can be found. The assets are long-term US government bonds, domestic stocks, foreign stocks, commodities, and the liabilities are from the pension scheme with nominal obligations and inflation adjusted (real) obligations. The column labeled average contains the average three year return, and the following column contains the annualized average. The same is done for the standard deviation. The columns with minimum and maximum contain the lowest returns on a consecutive three-year period. Panel B contains the correlation matrix ($\times 100$) of the assets and liabilities on a three-year basis. Panels C and D contain the same information, but then at a three month instead of three-year horizon, ranging from 1970:3 - 2001:12.

Panel A: three years	average	annual	stdev	annual	minimum	maximum
domestic gov-bonds	26.1	8.70	16.9	9.7	-18.7	68.0
domestic stocks	36.6	12.19	24.5	14.2	-41.5	87.1
foreign stocks	35.4	11.81	34.8	20.1	-27.2	137.9
commodities	32.7	10.91	36.4	21.0	-38.2	137.5
nominal liabilities	28.5	9.50	19.5	11.3	-17.6	79.8
real liabilities	26.9	8.96	7.7	4.4	6.8	43.9

Panel B: three years correlation matrix	domestic gov-bonds	domestic stocks	foreign stocks	commodities	nominal liabilities	real liabilities
domestic gov-bonds	100	51	34	-38	96	-39
domestic stocks	51	100	37	-51	47	-65
foreign stocks	34	37	100	-5	38	-10
commodities	-38	-51	-5	100	-30	52
nominal liabilities	96	47	38	-30	100	-32
real liabilities	-39	-65	-10	52	-32	100

Panel C: quarterly	average	annual	stdev	annual	mininum	maximum
domestic gov-bonds	2.21	8.84	5.3	10.6	-15.7	21.8
domestic stocks	2.76	11.04	7.7	15.5	-34.8	23.5
foreign stocks	2.62	10.48	8.7	17.4	-23.7	30.1
commodities	2.63	10.52	9.7	19.5	-36.6	43.9
nominal liabilities	2.18	8.72	6.7	13.5	-20.6	33.0
real liabilities	2.26	9.04	1.9	3.8	-3.4	10.5

Panel D: quarterly correlation matrix	domestic gov-bonds	domestic stocks	foreign stocks	commodities	nominal liabilities	real liabilities
domestic gov-bonds	100	29	13	-22	87	68
domestic stocks	29	100	59	-19	31	1
foreign stocks	13	59	100	-9	19	-8
commodities	-22	-19	-9	100	-18	0
nominal liabilities	87	31	19	-18	100	60
real liabilities	68	1	-8	0	60	100

Our sample period is from January 1970 to December 2001. In order to gain efficiency, we do not use 10 tri-annual observations, but make use of monthly overlapping tri-annual samples. Thus, the first observation is from Jan-1970 until Dec-1972, the second from Feb-1970 to Jan-1973, etcetera. This way, the number of observations is increased substantially. Since the error terms in a regression model with overlapping samples are by definition autocorrelated, we use the Newey & West (1987) method to account for heteroskedasticity and autocorrelation of general form. The interpretation of this correction method is that we take into account that we are using the same information several times.

We take as traditional assets the Ibbotson long-term government bond index, the MSCI USA (domestic stocks), and the MSCI EAFE (foreign stocks).[11] The alternative asset offered to the investor is the Goldman Sachs Commodity Total Return Index (GSCI). This is a fully cash-collateralized index of commodity futures; see Ankrim & Hensel (1993) for a description. This index reflects the return of an investor that is restricted to take full cash collateralization. In practice other assets than cash may serve as collateral for the futures which implies that the use of the GSCI yields a lower bound for the potential for commodity strategies. In Section 6.4.3 we analyze the impact of the assumption about the fully cash-collateralized commodity futures position. The use of the GSCI total return index is common in this line of literature, see Appendix A for a short summary. For reasons of brevity, we refer to this investment object simply as *commodities* in the remainder of this paper.

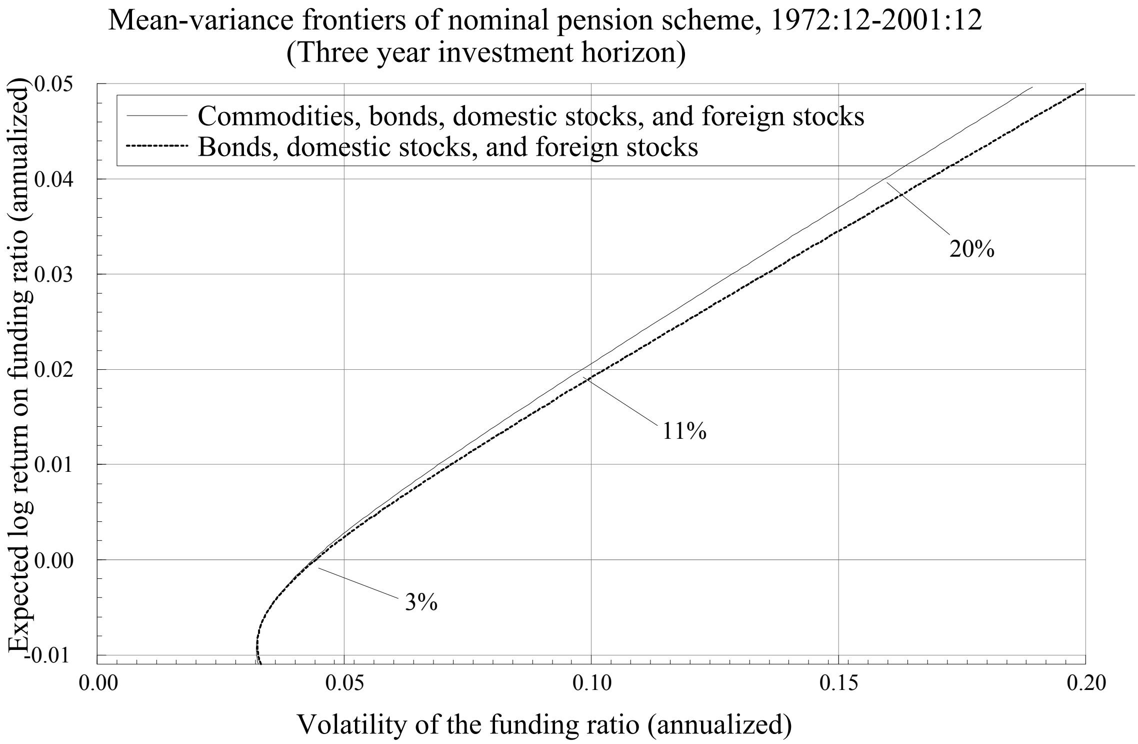
The descriptive statistics of the log returns on the assets are displayed in Table 6.1. Panel A and B contain the tri-annual, and Panel C and D the quarterly statistics. The highest average returns are obtained by investing in domestic stocks, which returned on average 12.2 percent over a three year horizon. Bonds have the lowest average return, 8.70 percent. Bond returns also have the lowest volatility, and commodity returns are the most volatile. The correlation matrix suggests a potential diversification benefit from investing in commodities, since correlations between commodities and traditional assets are negative at both horizons.

The descriptive statistics of the returns on the liabilities with a duration of 10 years can also be found in Table 6.1.[12] The correlations between the traditional assets and the liabilities are presented in Panels B and D. Note that because variables such as inflation rates and yields are highly autocorrelated, the covariance structure at the larger horizon differs substantially form the one at the quarterly horizon. From the correlation structure

[11]We also included the North American Real Estate Investment Trust (NAREIT) index, but this does not materially alter our results.

[12]The tri-annual returns on nominal liabilities are calculated as follows: $R_t = \left[(1+Y_t^{(7)})^3 - 1\right] - 10 \cdot \left(Y_t^{(7)} - Y_{t-36}^{(10)}\right)$, where the yields Y are expressed in annual terms, and t in months. The tri-annual returns on real liabilities are the aggregated monthly log returns of the Bridgewater index-linked bond return series.

Figure 6.1: Tri-annual mean variance frontiers of a pension scheme with nominal pension payments of 10-year duration. The vertical axis is the expected annual return on the funding ratio on a three-year strategic investment horizon. The horizontal axis is the volatility of the return on the funding ratio on an annual basis. The basis assets are long-term government bonds, domestic stocks, and foreign stocks. The sample period is Dec-1972 to Dec-2001. We use monthly overlapping tri-annual returns. At several points on the frontier the optimal portfolio weight of commodities is shown.



it becomes clear that future benefits defined in nominal or real returns matters for the correlation structure between assets and liabilities. Whereas over our sample period long-term government bonds correlate for 0.96 with nominal liabilities, the correlation with real liabilities is negative. This observation is crucial for our results. The opposite holds for the alternative asset class commodities, which correlates negatively with the nominal, but positive with the real liabilities. In fact, commodities are the *only* asset from our set with a positive correlation with real liabilities, indicating that inclusion of these assets can lead to risk reduction for pension schemes with real liabilities.

In Figure 6.1 the mean-variance frontiers for the nominal pension scheme are plotted. One frontier is constructed using only the three traditional assets, while the other frontier also allows investments in commodities. There is little difference in both frontiers, suggesting that the expected return of the funding ratio can hardly be increased with keeping the volatility equal. This is due to the close relation between the investments in government bonds and the nominal liability structure. Adding commodities leaves the efficient risk-return trade-off virtually unchanged. The expected return on the minimum variance portfolio is negative, indicating that investing in the lowest-risk strategy results in an expected deterioration of the solvency of the pension scheme.

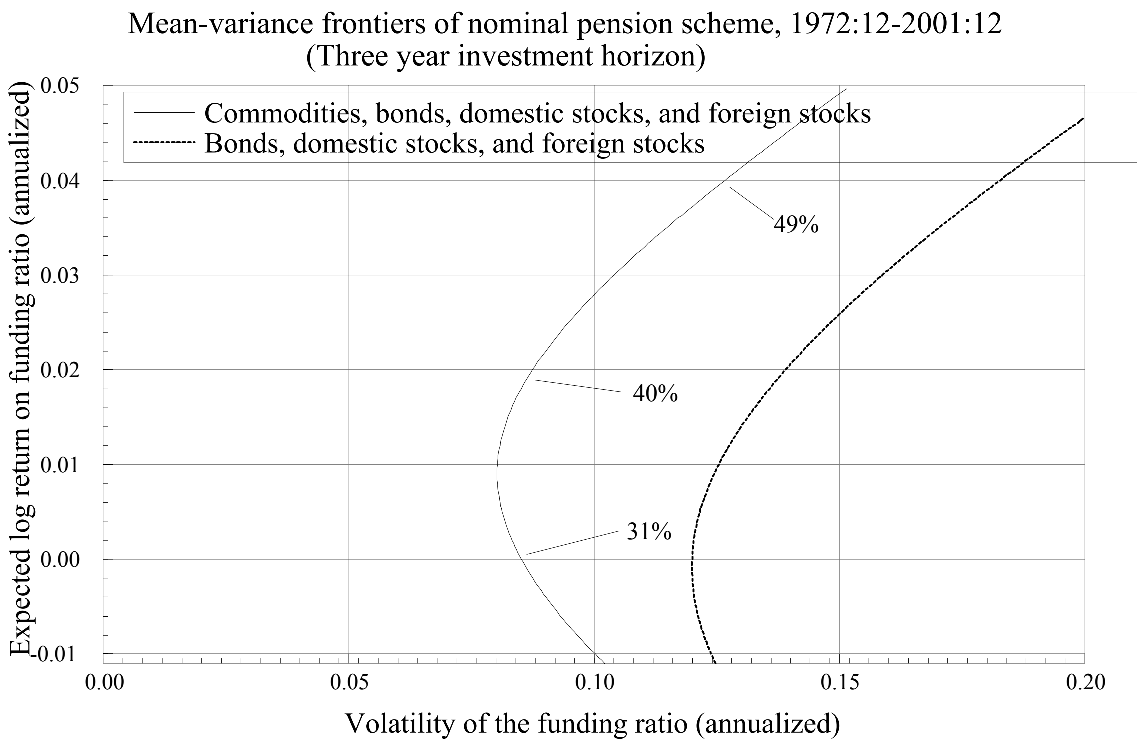
The mean-variance frontier of the stylized pension scheme with real benefits is depicted in Figure 6.2. This figure is different from the previous one in several respects. First, the expected return on the minimum-variance portfolio is positive, which means that for the portfolio with lowest funding ratio volatility the solvency of the scheme increases rather than decreases. Second, the volatility is much larger than for the nominal scheme, i.e. 14 percent versus 5 percent on a three year horizon. This is due to the mismatch between the value of the investable assets and the inflation-indexed pensions. Lastly, visual inspection suggests that while for nominal pension obligations the addition of commodities does not increase the investment opportunity set, for real pension schemes they provide additional diversification. The volatility of the funding ratio reduces in some cases even more than 30 percent.

At several points of the frontiers in Figure 6.1 and 6.2 the strategic weights to commodities in the new optimal portfolio are displayed. For the nominal pension scheme the weights are almost zero near the minimum-variance portfolio, and 20 percent at the expected return of 4 percent per annum. Even when the optimal weight is 20 percent, the volatility of the funding ratio seems to be reduced only marginally. The strategic weights in the inflation-index pension scheme are substantially higher on the efficient side of the frontier, amplifying the diversification benefits of commodities for all risk-averse investors.

We are not aware of papers investigating the properties of commodities in strategic asset allocation. Our qualitative results, however, are consistent with conclusions based on a short term investment horizon from Bodie (1980) and Froot (1995). These papers deal, however, with short term (annual or quarterly) asset-only investors and ignore possible correlation with the liability structure of the pension scheme.

The aforementioned papers lack to test for statistical significance of the shifts in the mean-variance frontier. Huberman & Kandel (1987) show how regression analysis can be used to perform these statistical tests. Such tests are equivalent with testing whether the optimal portfolio weight of the additional asset is significantly positive. The null hypothesis for *intersection* is that for a mean-variance investor with a given risk-aversion the optimal portfolio weight of the new asset is zero. The null hypothesis for *spanning* is that this new optimal weight is zero for all risk-aversions, and it can be shown that this hypothesis equals.

Figure 6.2: Tri-annual mean variance frontiers of a pension scheme with inflation-indexed pension payments of 10-year duration. The vertical axis is the expected annual return on the funding ratio on a three-year strategic investment horizon. The horizontal axis is the volatility of the return on the funding ratio on an annual basis. The basis assets are long-term government bonds, domestic stocks, and foreign stocks. The sample period is Dec-1972 to Dec-2001. We use monthly overlapping tri-annual returns. At several points on the frontier the optimal portfolio weight of commodities is shown.



$$H_0^{span} : \mu_{com} - \beta' \mu_R = 0 \quad \text{and} \quad \beta' \iota = 1, \tag{6.7}$$

where μ_{com} and μ_R are the expected returns on commodities and the basic assets, while β is the vector with covariances between the commodities and the traditional assets.

The hypothesis in (6.7) can be tested using the following linear regression equation,

$$R_t^{com} = \alpha + \beta' R_t^{basic} + \varepsilon_t, \tag{6.8}$$

where R_t^{com} is the return on commodities and R_t^{basic} is the vector of returns on the set of basic or traditional assets. Note that $\alpha = \mu_{com} - \beta' \mu_R$. Substitution of α in the null hypotheses for intersection and spanning gives the test in terms of the parameters of the regression equation. It is shown in, e.g. De Roon & Nijman (2001), that a modified version of this test can be used when the investor faces fixed liabilities. The only necessary alteration is that the liability return is subtracted from both the commodity and traditional returns.

We start by investigating whether commodity returns are spanned by the returns on the traditional assets by using regression equation (6.8). The results of this regression analysis are reported in Table 6.2. The p-value of the test statistic is 0.52 for the nominal scheme, confirming the intuition obtained from Figure 6.1 that the shift is insignificant. For the inflation-indexed scheme, the p-value of the test statistic is below 0.001, amplifying the economical significance of the difference in frontiers in Figure 6.2. Thus, our formal tests indicate that for real pension schemes commodities significantly improve the three year risk-return trade-off on the funding ratio, while this is not the case for pension schemes with nominal liabilities. The test statistic on spanning can be rewritten as the sum of two intersection hypotheses. The first is for an extreme risk-averse investor, and the second for a risk-neutral investor. We report both intersection tests also in Table 6.2, in order to examine which type of investor is driving the spanning rejection, and hence which type of investor can benefit most from investing in commodities. The last line of Table 6.2 suggests that, when spanning is rejected, this is mostly because the extremely risk averse investor can improve his risk-return trade-off significantly.

The above illustrates that if regulation does not allow pension funds to invest in alternative asset classes such as commodities, this might imply that the probability of underfunding is increased instead of decreased. Recalling that the asset labeled commodities in this paper actually is a dynamic (with an a priori fixed trading rule) derivatives trading strategy, this analysis suggests that the solvency of efficient pension funds can be harmed when regulators introduce restrictions on derivatives trading.

Table 6.2: **Mean-variance spanning of commodities for pension schemes.** The added asset is commodities, while the basic assets in the top panel are domestic bonds (bnd), domestic stocks (dom), foreign stocks (for), and in the bottom panel domestic real estate (nareit) is added as a basic asset. The parameter estimates are obtained by OLS on $R_t^{com} - R_t^{liab} = \alpha + \beta'(R_t^{basic} - R_t^{liab}) + \varepsilon_t$, where R_t^{com} is the commodity return, R_t^{liab} the return on the liabilities, and R_t^{basic} the vector with returns on the basic assets. The Newey and West (1987) standard errors (with lag 35) are displayed in the column behind the parameter estimate, and are used to calculate the spanning and intersection test statistics. With $\gamma \to \infty$ we test for intersection for an investor with extremely high risk aversion. In Panel A the results for the three-year, and in Panel B the three-month investment horizon are displayed. Sample periods are 1972:12–2001:12 and 1970:3–2001:12, respectively.

Panel A:

commodity spanning	nominal liabilities		inflation-indexed	
three year horizon	estimate	hac.se	estimate	hac.se
intercept	0.109	0.033	0.080	0.080
domestic gov-bonds	2.085	1.212	-0.338	0.246
domestic stocks	-0.495	0.548	-0.369	0.251
foreign stocks	0.340	0.277	0.135	0.138
number of obs.	349		349	
spanning test [p-val]	1.31	[0.52]	73.19	[0.00]
inters. $\gamma \to \infty$ [p-val]	1.07	[0.30]	63.39	[0.00]

Panel B:

commodity spanning	nominal liabilities		inflation-indexed	
three month horizon	estimate	hac.se	estimate	hac.se
intercept	0.003	0.009	0.004	0.007
domestic gov-bonds	1.068	0.222	-0.771	0.145
domestic stocks	-0.015	0.126	-0.126	0.088
foreign stocks	0.301	0.111	0.076	0.090
number of obs.	382		382	
spanning test [p-val]	4.09	[0.13]	93.14	[0.00]
inters. $\gamma \to \infty$ [p-val]	3.95	[0.05]	88.05	[0.00]

6.3 Short-term myopic and tactical asset allocation

In this section we relax the assumption of a three-year buy-and-hold asset allocation and investigate the short-term benefits of investing in commodities. We start this section by an unconditional test for spanning on a three-month investment horizon. Next, we analyze whether information about the state of the economy might improve the conditional frontier, by allowing expected asset returns and covariances to change depending on these variables. We end this section by examining the potential benefits of short-term timing strategies between stocks and bonds on the long-term frontier. This answers the question whether such tactical timing strategies are useful in addition to a three-year buy-and-hold strategy in bonds, domestic stocks, foreign stocks, and commodities.

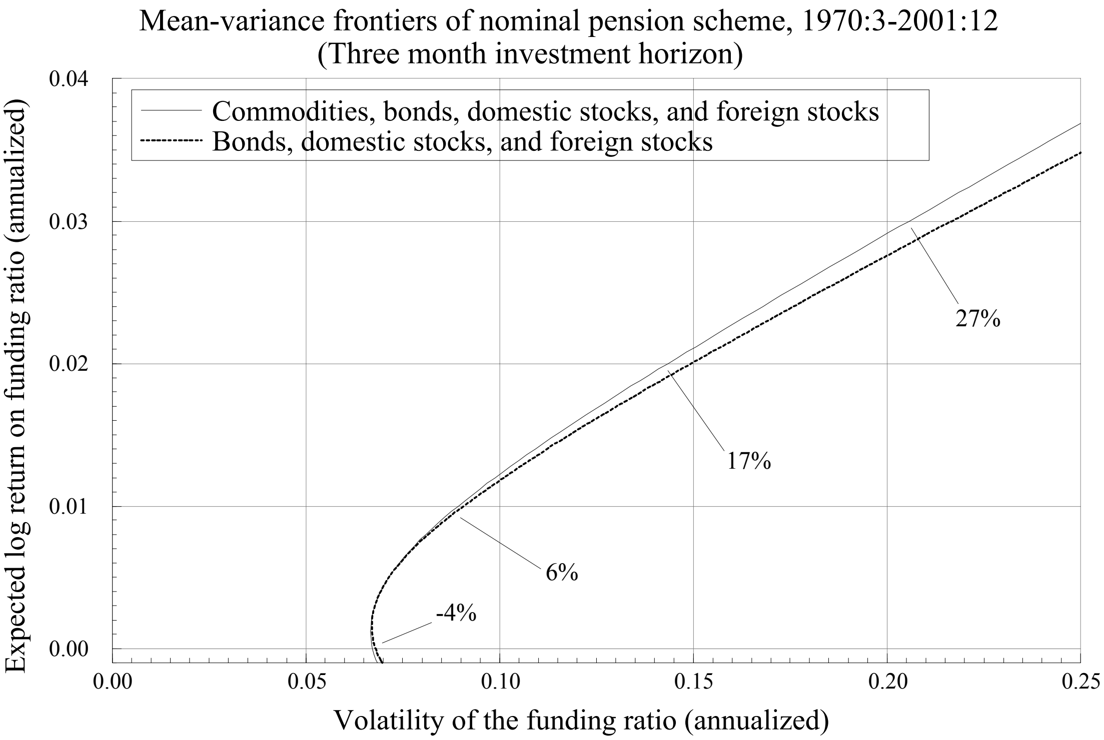
Though pension schemes have in principle a long term objective, their performance is mostly evaluated at shorter horizons too. The short horizon perspective is particularly important for asset managers, whose incentives are usually based on short term (relative) performance. In addition, regulatory bodies require that the probability of underfunding in the short run should be at reasonable levels. We examine whether the efficient short term (quarterly) mean-variance frontier is spanned by the traditional asset classes when the liability structure is also taken into account. These results from spanning on the short and long term (buy-and-hold) investments may be different due to changing covariance structures at various horizons. The short term persistence in inflation in particular causes this horizon effect in covariance structure.[13] The quarterly horizon analysis is performed unconditionally as well as by a model that allows expected returns and covariances to vary depending on conditional macro economic information.

The descriptive statistics of the quarterly returns can be found in Table 6.1, Panel C and D.[14] The most noteworthy is the correlation structure in Panel D, which is different from the tri-annual returns for the pension scheme with real liabilities in Panel B. The correlation with long-term government bonds has become positive, while the correlations with the other assets is close to zero. The correlation between the nominal and real liability returns is also positive, compared to a negative for the three-year horizon. This change in correlation structure, due to the fact that the return on real liabilities is far from uncorrelated, may lead to different optimal asset allocations for the myopic short term investor than for a strategic investor with a three year horizon.

[13] A regression of the three-month index-linked bond return on its three-month lag (and a constant) results in an insignificant estimate of -0.02 (t-value: -0.24), while a regression of the three-year index-linked bond return on its three-year lag (and a constant) yields a significant estimate of 0.43 (t-value: 3.70).

[14] For the return on the nominal liabilities we have now taken both the 10-year yield and not the 9.75-year yield as is required. In the previous example we used the 7-year yield when needed. We expect the yields for this short duration difference to be so close that the results are not influenced by this approximation.

Figure 6.3: Quarterly mean variance frontiers of a pension scheme with nominal pension payments of 10-year duration. The vertical axis is the expected annualized return on the funding ratio on a quarterly strategic investment horizon. The horizontal axis is the volatility of the return on the funding ratio on an annual basis. The basis assets are long-term government bonds, domestic stocks, and foreign stocks. The sample period is Mar-1970 to Dec-2001. We use monthly overlapping quarterly returns. At several points on the frontier the optimal portfolio weight of commodities is shown.



In Figure 6.3 and 6.4 we depict the mean-variance frontier of the nominal and real pension scheme, respectively. Inclusion of commodities as an asset class shifts the mean-variance frontier only marginally to the left for the pension scheme with nominal liabilities, while it shifts substantially to the left for the real liability scheme. Again, we conduct a statistical test to investigate whether the shifts in the frontier are statistically significant. The conclusions from the visual inspection of the graphs are statistically confirmed, with a p-value of 0.13 for the nominal case, and below 0.001 for the real case. Thus, even when the correlation between the real liabilities and government bonds has increased substantially, investing in commodities has a significantly positive impact on the risk-return trade-off for the real pension scheme. This is consistent with the findings of for example Froot (1995), who investigates the diversification properties of commodities to an *asset-only* portfolio of stocks and bonds on a quarterly horizon. He finds that commodities are better diversifiers than real estate and equity of commodity-related firms.

Thus far, we have investigated the unconditional mean-variance frontier, which implies that only investment strategies that can be fixed a priori and do not use the most recent information about the state of the economy are considered.[15] There is a large body of literature claiming that asset returns are predictable up to a certain degree. Moreover, the covariances of asset returns might depend on specific economic circumstances (see, e.g., Campbell (2000) for an overview on asset return predictability). We allow expected asset returns and covariances to vary depending on the economic situation; see, e.g., Shanken (1990), and test whether efficient investment strategies can exploit time variation in these quantities.

The conditioning information we use in order to characterize the economic situation is the yield on a 10-year government bond, the term spread, the default spread, and the inflation rate. Similar economic information is also used in, e.g., Ferson & Schadt (1996). The term spread is defined as the yield of a 10-year government bond minus the yield of a 1-year government bond. The default spread is defined as the Moody's seasoned Baa corporate bond yield minus the Moody's seasoned Aaa corporate bond yield. These yield data are obtained from the Federal Reserve Bank of St Louis. We construct annual inflation rates on a monthly basis using the same methodology as the Bureau of Labor Statistics. Hence, our results for December correspond to the annual inflation rate as is published each year. We incorporate a reporting lag of one month in our studies, since the inflation rate is typically published with a delay. The descriptive statistics on our conditioning variables can be found in Table 6.3. The difference between the average nominal yield and the average inflation is three percent per annum. During some period

[15] Cochrane (2001) refers to this frontier the unconditional *fixed-weight* mean-variance frontier, since it does not contain managed portfolios.

Figure 6.4: Quarterly mean variance frontiers of a pension scheme with real pension payments of 10-year duration. The vertical axis is the annualized expected return on the funding ratio on a quarterly strategic investment horizon. The horizontal axis is the volatility of the return on the funding ratio on an annual basis. The basis assets are long-term government bonds, domestic stocks, and foreign stocks. The sample period is Mar-1970 to Dec-2001. We use monthly overlapping quarterly returns. At several points on the frontier the optimal portfolio weight of commodities is shown.

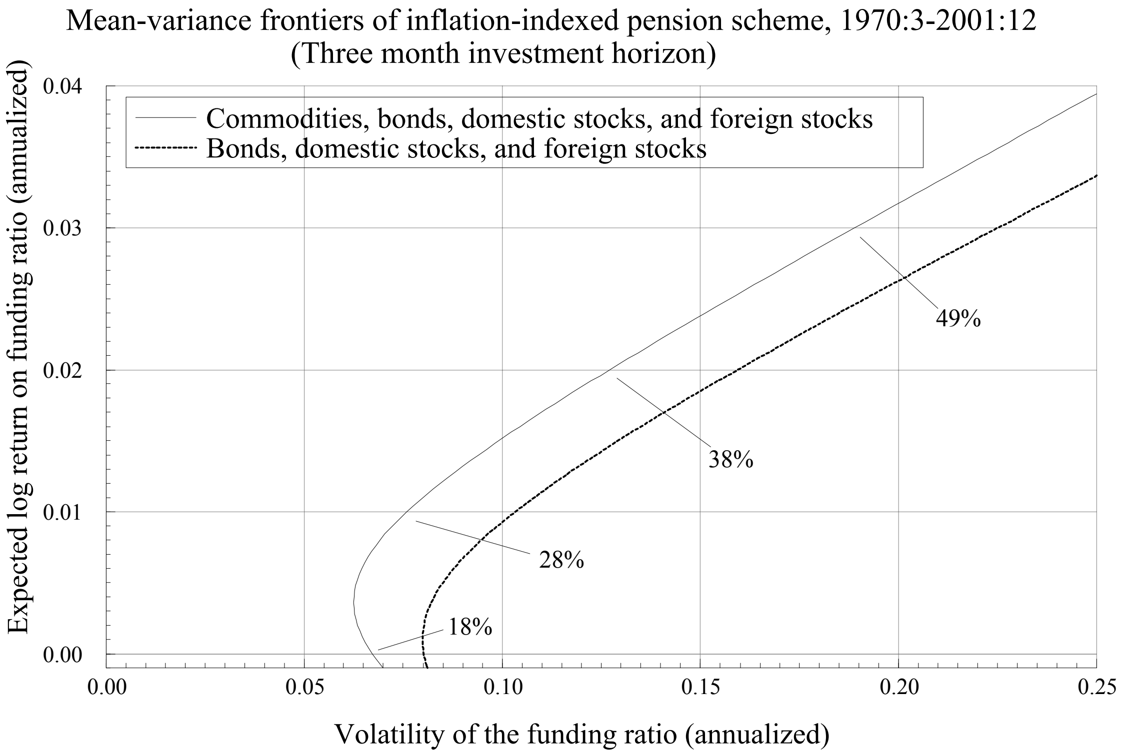


Table 6.3: **Descriptive statistics of conditioning variables, 1970:1 - 2001:12**. This table contains the monthly average, standard deviation, minimum, and maximum of the macro economic variables. The bond yield is the level of the 10-year government bond yield. The term spread is defined as the yield of a 10-year government bond minus the yield of a 1-year government bond. The default spread is defined as the Moody's seasoned Baa corporate bond yield minus the Moody's seasoned Aaa corporate bond yield. Monthly inflation is calculated in similar fashion to the Bureau of Labor Statistics calculates its annual inflation, so that the December values correspond to the officially announced annual inflation rate.

monthly	average	stdev	mininum	maximum
bond yield	8.08	2.31	4.53	15.32
term spread	0.88	1.11	-3.07	3.29
default spread	1.09	0.44	0.55	2.69
inflation	4.97	2.78	1.54	12.75

of our sample, an inverse term structure could be observed, since the minimum term spread is negative.

Conditional spanning can also be tested for by using regression analysis. The regression equation suitable for this type of conditional spanning is

$$R_t^{comm} = \alpha_0 + \alpha_1' Z_{t-1} + \beta_0' R_t^{basic} + \beta_1' \left(Z_{t-1} \otimes R_t^{basic} \right) + \varepsilon_t, \tag{6.9}$$

where Z_{t-1} is a vector with macro economic variables known at the end of period $t-1$, and β_1 a 15-dimensional vector with coefficients of the cross-products between the basic assets and the macro-economic variables. This regression allows to test for the validity of the restrictions implied by conditional spanning, which are

$$\text{conditional spanning: } H_0 : \alpha_0 + \alpha_1' Z_{t-1} = 0, \quad \beta_0' \iota + \beta_1' \left(Z_{t-1} \otimes \iota \right) = 1. \tag{6.10}$$

Testing for spanning for all economic situations means means that

$$\text{conditional spanning: } H_0 : \alpha_0 = 0, \quad \alpha_1 = 0, \quad \beta_0' \iota = 1, \quad \beta_1 = 0. \tag{6.11}$$

Tests for conditional spanning indicate whether it is efficient to include commodities in the portfolio given the current economic situation. We estimate the regression model of (6.9) and test the hypotheses in (6.10) and (6.11) in order to investigate whether allowing for conditional expected return and covariances changes the benefits from investing in commodities. For the ease of presentation, we report the results for the economic situation at the end of each five-year period of our sample. Table 6.4 contains the parameter estimates as well as spanning tests. These results indicate that the mean-variance frontier

Table 6.4: **Conditional spanning with time-varying expected returns and covariances**. The estimated regression equation is $r_t = \gamma_0 + \gamma' Z_{t-1} + \beta_0' R_t + \beta' (Z_{t-1} \otimes R_t) + \varepsilon_t$, where r_t is the commodity return, the conditioning information Z_{t-1} consists of the long yield, term spread, default spread, and inflation, and R_t are the returns on long bonds, domestic stocks, and foreign stocks. Since we use monthly overlapping quarterly returns, the standard errors are corrected using the Newey and West (1987) method. The sample period is May-1970 – Dec-2001. The following rows contain the values of the conditioning variables at the end of five-year periods, for which the p-value for a spanning test under these conditions is presented in the final two columns. The null hypothesis for spanning implies that $\gamma_0 + \gamma' Z_{t-1} = 0$ and $\beta_0' R_t + \beta' (Z_{t-1} \otimes \iota) = 1$. The null hypothesis to check for spanning for all economic situation is $\gamma_0 = \gamma = \beta = 0$, and $\beta_0' \iota = 1$.

Spanning	yield	term	default	inflation	p-value nom	p-value real
Dec-1974	7.43	0.12	1.74	10.21	0.49	0.00
Dec-1979	10.39	-1.59	1.32	10.35	0.16	0.00
Dec-1984	11.50	2.17	1.27	4.16	0.00	0.00
Dec-1989	7.84	0.12	0.96	4.67	0.04	0.00
Dec-1994	7.81	0.67	0.64	2.58	0.04	0.00
Dec-1999	6.28	0.44	0.64	2.08	0.08	0.00
	Under all economic situations				0.00	0.00

shifts significantly outward for the inflation-index pension scheme for each of the economic circumstances that we analyze.

For the nominal scheme, we observe some differences by introducing conditioning information. Whereas the unconditional mean-variance frontier of the traditional asset spans the set including commodities, this does not hold for the conditional mean-variance frontier at each of the periods under investigation. In 1984 and 1989, the spanning test is rejected at the five percent significance level. In other words, the investment opportunity set created by the three basis assets can be expanded by introducing the alternative assets commodities. For example, in the end of 1984, the high term spread and low inflation cause commodities to have a low conditional expected return. This low conditional expected return, in combination with the estimated covariance structure, causes the mean-variance spanning hypothesis to be rejected. From this model to incorporate conditional information, it follows that in certain economic environments short term asset allocation may contain commodities, while at a strategic horizon commodities should not be included. We observe this for the pension scheme with nominal claims. For a pension scheme with real claims investing in commodities seems to be beneficial both on the long and short run, both unconditionally and conditionally.

In the remainder of this section, we examine whether active short-run tactical allocation between stocks and commodities increases the strategic buy-and-hold mean-variance frontier including commodities. This provides an answer to the question whether there

Table 6.5: **Quarterly timing strategies 1970-2001.** P-values for quarterly timing strategies between stocks and bonds. These p-values correspond to the hypothesis that a quarterly timing strategy between stocks and commodities does not shift the three-year mean-variance frontier to the left.

timing strategy	nominal	real
bond yield	0.00	0.97
inflation	0.11	0.03
term spread	0.00	0.00
default spread	0.00	0.00

are possible longer-horizon gains to engage in tactical allocation based on macro-economic news. These dynamic trading strategies (or managed portfolios) can be interpreted as new asset classes, on which the pension scheme can decide to invest in or not.

We use the same four macro variables as above to investigate the effects of timing between stocks and commodities.[16] We normalize the variables for ease of interpretation by subtracting the mean and dividing by the standard deviation. This normalized variable is the signal for the timing strategy.[17] A signal with value 1 means that a long position in commodities is taken, which is financed by a short position in the stock market. We simultaneously evaluate all possible combinations of linear strategies in the bond yield, term spread, default spread, and inflation rate. This can be done by checking whether the four timing strategies based on a single macro variable are simultaneously spanned by the traditional buy-and-hold portfolio, which now also contains a fixed strategic position in commodities. Similar active trading strategies for currency futures have been investigated by De Roon, Nijman & Werker (2003).

The spanning hypothesis for adding quarterly timing strategies to a strategic portfolio on a three year horizon based on the inflation rate, default spread, term spread, and bond yield, is rejected with a p-value below 0.001 for both the nominal and real pension scheme. This means that quarterly timing strategies between commodities and stocks based on these macro economic variables enhance the efficient risk-return trade-off for pension schemes significantly. The excess returns of the strategies based on the single variables are in Table 6.5. The p-values of the spanning tests for each of the variables separately is also tabulated, and indicates that timing on the basis of the term spread and

[16]In addition, we also performed a test on the timing strategy proposed by Johnson & Jensen (2001), using conditioning information about restrictive or expansive policies by the Federal Reserve. The spanning hypothesis is rejected for both the real and nominal pension schemes when bonds, domestic stocks, and foreign stocks are the basic assets. However, when domestic real estate is added the spanning hypothesis is no longer rejected. Results of these additional tests are available from the authors upon request.

[17]The investment strategy is $\frac{z_{i,t}-\bar{z}_i}{\sigma_i(z)} \cdot R^e_{t+1}$, where $z_{i,t}$ is the value of the macro economic variable i at time t, and R^e_{t+1} is the excess return of commodities over the stock market.

default spread is expanding the efficient set for both the nominal and real pension scheme, and the inflation rate and yield are only significant for one type of the liabilities.

6.4 Robustness and extensions

In this section, we address some issues of robustness and some possible extensions for further research. In the first subsection the analyses are repeated for the post 1984 subperiod, which is characterized by more modest inflation than the first 15 years of our sample. We also use an alternative commodity index, computed by the Commodity Research Bureau (CRB), to examine whether our results are dependent on the choice of commodity index. In the second subsection we briefly address the issue of cash as the futures collateral. The third subsection addresses how to test for spanning when the utility function of the investor is not the usual mean-variance utility function.

6.4.1 Subperiod analysis 1984-2001

Since Paul Volcker became the chairman of the Board of Governors of the Federal Reserve system in 1979, the central bank's target has become to keep inflation under control. Since this policy is likely to continue in the future, the first part of our sample period might not be representative. We decide to investigate the subsample ranging from January 1984 – December 2001 in order to examine the influence of this period characterized by high inflation. First, we investigate whether there is spanning on the strategic three year horizon. Next, we check whether there is spanning for the myopic investor with an investment horizon of three months. Finally, we investigate the benefits of timing strategies in addition to strategic allocations.

The descriptive statistics over the subperiod are displayed in Table 6.6. The regression results used to test for spanning can be found in Table 6.7. The conclusions for the strategic three year horizon are similar to the entire sample period. Spanning cannot be rejected for the pension scheme with nominal interest rates, but spanning is rejected for the inflation-indexed pension scheme.

For the myopic short term investor with real liabilities the results are qualitatively the same as before. However, when nominal liabilities are concerned, the spanning hypothesis is rejected at the 10 percent level for this subperiod, indicating that for myopic pension schemes with nominal liabilities commodities are also expanding the MVE frontier.

6.4.2 Alternative commodity index

For the shorter sample period 1984-2001, we can also use the Commodity Research Bureau (CRB) total return index to check for robustness on the choice of commodity index. The

Table 6.6: **Descriptive statistics subperiod analysis.** In Panel A, the tri-annual log returns (in US dollars) over the sample 1987:1 - 2001:12 can be found. Panels C and D contain the same information, but then at a three month instead of three-year horizon, ranging from 1984:3 - 2001:12. In addition, descriptive statistics of the alternative commodity index CRB are provided as well.

Panel A: three years	average	annual	stdev	annual	minimum	maximum
domestic gov-bonds	30.73	10.24	11.3	6.5	9.39	66.30
domestic stocks	46.90	15.63	20.6	11.9	-6.02	87.10
foreign stocks	34.90	11.63	39.1	22.6	-27.23	137.91
commodities	27.08	9.03	31.1	18.0	-38.24	95.80
commodities CRB	11.27	3.76	17.8	10.3	-24.17	42.42
nominal liabilities	32.19	10.73	14.8	8.6	7.88	79.82
real liabilities	22.10	7.37	5.6	3.2	6.81	31.30

Panel B: 3Y correlation	bonds	domstock	forstock	GSCI	CRB	nomliab	realliab
domestic gov-bonds	100	36	47	-7	-10	95	45
domestic stocks	36	100	29	-30	-10	25	-45
foreign stocks	47	29	100	-2	24	49	9
commodities	-7	-30	-2	100	65	1	63
commodities CRB	-10	-10	24	65	100	-12	37
nominal liabilities	95	25	49	1	-12	100	51
real liabilities	45	-45	9	63	37	51	100

Panel C: Quarterly	average	annual	stdev	annual	minimum	maximum
domestic gov-bonds	2.74	10.96	5.0	9.9	-10.15	18.01
domestic stocks	3.41	13.64	7.6	15.2	-34.84	20.43
foreign stocks	2.67	10.67	8.9	17.8	-23.74	30.08
commodities	1.86	7.45	8.9	17.9	-22.30	43.93
commodities CRB	0.59	2.34	4.4	8.7	-12.38	11.68
nominal liabilities	2.78	11.13	5.8	11.5	-12.50	20.68
real liabilities	1.92	7.67	1.7	3.3	-3.45	6.06

Panel D: Q correlation	bonds	domstock	forstock	GSCI	CRB	nomliab	realliab
domestic gov-bonds	100	21	17	-23	-29	88	77
domestic stocks	21	100	58	-15	-8	24	2
foreign stocks	17	58	100	1	19	24	-2
commodities	-23	-15	1	100	67	-25	2
commodities CRB	-29	-8	19	67	100	-32	-15
nominal liabilities	88	24	24	-25	-32	100	70
real liabilities	77	2	-2	2	-15	70	100

descriptive statistics of this alternative commodity index can be found in Table 6.6. The results from this commodity index amplify the results from our analysis. In Panels A and B of Table 6.7 the results can be found. The spanning hypothesis is again rejected on both the quarterly and three year horizon, indicating that the empirical evidence for the addition of commodities to the investor's portfolio is not due to the choice of the particular commodity index.

6.4.3 Futures positions without cash-collateral

In accordance with the existing literature, we use the fully cash-collateralized total return index as the commodity asset in this paper. In practical situations, however, other assets in the portfolio may also serve as collateral for the commodity futures positions. An alternative and more extreme view is to assume that no cash-collateral whatsoever is needed, i.e., the assets in the existing portfolio may always serve as collateral for the commodity future positions. This changes the analysis as presented above, because a futures return is not a true return, since no initial investment is required. In addition to the true returns on the asset side and the fixed liabilities, the return on the funding ration now also consists of the excess return from the futures position.

The regression-based spanning tests used in the previous sections can be straightforwardly generalized for portfolios containing futures positions; see De Roon et al. (2003), amongst others. The results from this robustness analysis confirm our previous findings.[18] The spanning hypothesis on the three-year horizon cannot be rejected for the nominal pension scheme (with p-value 0.11). For the inflation-indexed pension scheme, spanning is rejected (with p-value < 0.001), implying that the shift in the mean-variance frontier by adding commodity futures is not due to the cash-collateralization assumed in the previous sections.

6.4.4 Non-mean variance utility functions

In the analyses of this paper, we have assumed that the pension scheme has a mean-variance utility function in the funding ratio. If the returns on the assets and liabilities are not normally distributed (which is an approximation at best) the mean-variance approach is restrictive and the optimal asset allocation will depend on the utility function of the investor. A power utility function with a large risk aversion parameter might well characterize the preferences of an investor that puts a lot of weight on assuring a funding

[18]For reasons of brevety, we do not report the full table with results from this analysis. These tables are available from the authors upon request.

Table 6.7: **Robustness of results for subsample 1984–2001 and CRB index.** This table is the equivalent of Table 6.2, but now for the sample period 1984–2001. Panel A contains the results for the three-year horizon, and Panel B for the three-month horizon. This is done for both the GSCI and CRB total return index.

Panel A:

	GSCI strategic				CRB strategic			
Sample: 1984-2001	nominal liabilities		real liabilities		nominal liabilities		real liabilities	
Horizon: Three year	estimate	hac.se	estimate	hac.se	estimate	hac.se	estimate	hac.se
intercept	0.030	0.165	0.181	0.124	-0.150	0.063	-0.083	0.056
domestic gov-bonds	1.849	1.512	-1.304	0.396	2.884	0.584	-1.168	0.265
domestic stocks	-0.363	0.517	-0.131	0.263	-0.149	0.238	0.199	0.155
foreign stocks	-0.026	0.159	0.107	0.143	0.166	0.077	0.202	0.042
spanning test	0.16	[0.92]	53.00	[0.00]	35.86	[0.00]	542.39	[0.00]
inters. $\gamma \rightarrow \infty$ [p-val]	0.14	[0.70]	36.30	[0.00]	12.91	[0.00]	51.46	[0.00]

Panel B:

	GSCI myopic				CRB myopic			
Sample: 1984-2001	nominal liabilities		real liabilities		nominal liabilities		real liabilities	
Horizon: Quarterly	estimate	hac.se	estimate	hac.se	estimate	hac.se	estimate	hac.se
intercept	-0.009	0.011	0.009	0.009	-0.022	0.007	-0.008	0.004
domestic gov-bonds	1.222	0.276	-0.974	0.179	1.083	0.181	-0.634	0.106
domestic stocks	0.046	0.145	-0.202	0.123	0.095	0.120	-0.094	0.059
foreign stocks	0.319	0.130	0.194	0.088	0.317	0.099	0.220	0.045
spanning test	4.99	[0.08]	67.17	[0.00]	20.73	[0.00]	222.13	[0.00]
inters. $\gamma \rightarrow \infty$ [p-val]	4.65	[0.03]	57.43	[0.00]	8.53	[0.00]	166.15	[0.00]

ratio that is at least equal to one.[19]

Spanning for more general utility functions than the standard mean-variance case can be dealt with in a regression framework as well. For *generalized spanning*, the regression equation (6.8) changes to

$$r_t = \alpha + \beta' R_{t+1} + \sum_i \gamma_i U_i'(\phi_i^{*\prime} R_{t+1}) + \varepsilon_{t+1}, \tag{6.12}$$

where $U_i'()$ denotes the derivative of the i^{th} utility function. The scaled optimal portfolio weights for investors with non-mean-variance utility are denoted by ϕ_i^*. Generalized spanning restrictions imply, next to the usual $\alpha = 0$ and $\beta'\iota = 1$ for each asset, that $\gamma_i = 0$ for all i. For a more detailed derivation of the hypotheses and tests from this section see, e.g., the survey article by De Roon & Nijman (2001).

In addition to the mean-variance utiltiy function, we use power utility functions with various degrees of weights on negative returns on the funding ratio to investigate the benefits of commodities in the institutional portfolio. The results of the spanning tests are displayed in Table 6.8. When a utility function with high aversion to negative returns on the funding ratio ($\rho = 15$) is investigated, spanning at the quarterly horizon is rejected for both the nominal and inflation-indexed pension scheme. Thus, pension schemes that are more averse to negative returns on their funding ratio have even more reason to add commodities to increase efficiency of their portfolios. So, extending our set of utility functions with power utility functions yields that investing in commodities can be also efficient for a nominal pension scheme with high aversion to negative returns.

6.5 Conclusions

In this paper we analyze the benefits for pension schemes to invest part of their wealth in commodities. We leave the traditional asset-only framework and incorporate market-based returns for both nominal and inflation-indexed liabilities. Our results indicate that for nominal pension schemes the use of commodities is limited, while for real pensions they reduce the volatility on the funding ratio more than 30 percent. In addition to the significant economic magnitude of this risk reduction, we contribute to the existing literature on commodity investments by providing statistical significance as well.

Our analysis aims in the first place at a strategic three year buy-and-hold investment horizon. Since the returns on the real liabilities are correlated over time, this might lead to different allocations than for an investor with a short, say quarterly, investment horizon. While our unconditional results remain unchanged for the short term, there is

[19] A power utility function has the form $u(W) = \frac{W^{1-\rho}-1}{1-\rho}$, with W the future wealth, defined as $1 + R \cdot w$, where R are the expected returns on the assets, and w the corresponding portfolio weights.

Table 6.8: **Non-mean-variance spanning.** This table contains the p-values of mean-variance spanning tests, as well as tests for power utility spanning in addition to mean-variance spanning. The power utility function is given by $u(W) = \frac{W^{1-\rho}-1}{1-\rho}$, where future wealth W is defined as $1 + R \cdot w$, where R are the asset returns, and w the corresponding weights in the portfolio. Regression equation $R_t^{com} - R_t^{liab} = \alpha + \beta'(R_t^{basic} - R_t^{liab}) + \gamma \cdot u'\big(\big(R_t^{basic} - R_t^{liab}\big) \cdot \widehat{\varphi}\big) + \varepsilon_t$ is estimated, and the hypothesis for generalized spanning is $\alpha = \gamma = 0$ and $\beta'\iota = 1$. In the regression equation, $\widehat{\varphi}$ is the adjusted optimal weights vector. The covariance matrix is corrected for overlapping samples and heteroskedasticity using the Newey and West (1987) method.

Horizon	Three month		Three year	
p-values	nominal	real	nominal	real
mv-span	0.14	0.00	0.55	0.00
$\rho = 1$	0.23	0.00	0.01	0.00
$\rho = 3$	0.25	0.00	0.00	0.00
$\rho = 6$	0.03	0.00	0.36	0.00
$\rho = 15$	0.00	0.00	0.07	0.00

no conditional spanning for both the nominal and real pension scheme. Thus, in certain economic situations, also for nominal pension schemes with a short horizon commodities improve the efficient risk-return trade-off.

Finally, we investigate whether timing strategies between commodities and stocks are improving the strategic mean-variance frontier even further. We find that the timing strategies based on macro economic information may expand the three-year horizon frontier significantly.

Our results are robust for the choice of sample period, as our results over the 1984-2000 period suggest. Our results do not seem to depend on our choice of commodity index either. The empirical results against spanning are even stronger for an alternative commodity index which is available over the 1984-2000 period. As a final robustness check, we have extended the usual set of mean-variance utility functions with power utility functions, to capture the non-normalities in the returns on assets and liabilities. Addition of these functions do not affect our previous results.

The liability hedge potential of alternative asset classes such as commodities should also be taken into account by regulators. The call for more strict regulation on the use of alternative assets by institutional investors has become stronger, especially in Europe. Our results suggest that the presence of alternative assets (which are frequently constructed by combinations of derivative products) could protect the solvency position of the fund, and hence benefit the participant in the fund. The merit of alternative assets in strategic asset allocation should be confronted with the other assets in the portfolio, and the liability structure of the scheme.

Table 6.9: **Other research on commodity investing**

Paper	Commodity Index	Frequency
Bodie (1980)	raw futures data	annual
Ankrim & Hensel (1993)	GSCI, ICI	monthly
Lummer & Siegel (1993)	GSCI	annual
Froot (1995)	GSCI, CRB	quarterly
Becker & Finnerty (1997)	GSCI, CRB	monthly, quarterly
Anson (1999)	GSCI, CPCI, ICI, JPMCI	quarterly
Johnson & Jensen (2001)	GSCI, JPMCI	monthly
Georgiev (2001)	GSCI	monthly

Figure 6.5: Composition of the Goldman Sachs Commodity Index at 7 December 2001

Table 1: GSCI Components and Dollar Weights (%)(December 7, 2001)

Energy	57.75	Industrial Metals	7.90	Precious Metals	2.83	Agriculture	20.55	Livestock	10.97
Crude Oil	24.72	Aluminium	4.18	Gold	2.35	Wheat	5.10	Live Cattle	7.67
Brent Crude Oil	11.34	Copper	2.10	Platinum	0.24	Red Wheat	1.67	Lean Hogs	3.30
Unleaded Gas	4.44	Lead	0.31	Silver	0.24	Corn	5.50		
Heating Oil	6.17	Nickel	0.54			Soybeans	2.49		
GasOil	2.96	Tin	0.11			Cotton	1.82		
Natural Gas	8.13	Zinc	0.67			Sugar	2.37		
						Coffee	0.70		
						Cocoa	0.41		
						Orange Juice	0.50		

A The Goldman Sachs Commodity Index

The Goldman Sachs Commodity Index (GSCI) is a composite index of five commodity sectors.[20] The returns are unleveraged, fully cash-collateralized long-only investments in commodity futures with full reinvestment. The individual components are determined on the basis of liquidity and are weighted by their respective world production quantities. A table of the weights in the index in December 2001 can be found in Figure 6.5. The GSCI has been used in many recent papers studying commodity investments. A summary of this research can be found in Table 6.9. We display for each of the papers the commodity index used and the frequency of the analysis.

[20]More information can be found at the website of Goldman Sachs, `www.gs.com/gsci`.

Part III

Mutual fund style and performance measurement

Chapter 7

Return-based style analysis with time-varying exposures

7.1 Introduction

The investment style of a mutual fund is not always clear for investors not acquainted with its manager or the philosophy of the fund family it belongs to. Due to the large number of mutual funds these days, it is almost impossible for an investor to grasp all information regarding their investment styles. Although the investment style of a mutual fund potentially has many dimensions, in our view its sensitivities to risk factors are the most relevant for investors.[1] These sensitivities, or exposures, gauge the effect of the return on the style or risk factor on the return of the mutual fund. For a potential investor in mutual funds, a tool introduced by Sharpe (1992) might be appropriate to get a first impression of the historical exposures of the fund. These can be used to determine the benefits of investing in the fund, for example by predicting style exposures, or analyzing the manager's skills. Sharpe's method for analyzing mutual funds is known as *return-based style analysis* (RBSA). Basically, RBSA is constrained regression of the returns of the mutual funds on relevant style indices.

In academic research, variants of RBSA are used in several applications. These applications include the classification of mutual funds, performance evaluation conditional on investment style, and optimal portfolio choice for fund of funds.[2] In this paper, we aim to improve the accuracy of the estimation or prediction of style or risk exposures by using fund and index returns only and a valid statistical model. Whereas stylized examples

[1]Other style dimensions include the fee structure, the self-declared investment objective, the use of derivative products, the investment process.

[2]An application in which an investor chooses an optimal portfolio of mutual funds using RBSA can be found in DeRoon, Nijman & TerHorst (2003).

indicate that our method is more advantageous in several circumstances, the empirical applications are somewhat less convincing.

A major drawback of RBSA in its original form is the basic assumption that the investment style of a fund remains fixed over the sample period. The use of so called *rolling regressions* alleviates this drawback to a certain extent. In a rolling regression the investment style is not fixed over the entire sample period but over a given estimation window. In empirical work, the length of this window is often chosen to lie somewhere between 24 and 60 months. This window is shifted month by month over the entire sample period. There is no theoretical argument that defends the use of rolling estimation windows when styles vary over time. In practice the use of rolling windows causes a sub-optimal use of the data by picking an ad hoc window size. Funds that change their exposures frequently require a shorter window, while for funds with fixed exposures the use of a longer window generates more precise exposure estimates. A method with an endogenously determined weighting scheme for historical observations alleviates this problem of choosing a window size. The Kalman filter is a method that endogenizes the weighting scheme.

In this paper, we contribute to the discussion by *explicitly modeling time variation* in the investment style of a mutual fund. In order to estimate this dynamic model, we use the *Kalman filter* approach, which has several advantages over standard regression techniques. The main advantage for this application is the more efficient use of available information, while allowing for time variation in exposures. Throughout this paper, we distinguish between the Kalman *filter* and Kalman *smoother*. The difference between the two is the conditioning information set. The filter is conditional on information up to time t and thus more appropriate for prediction, while the smoother is conditional on the entire sample, and hence more suited for descriptive purposes. We examine several applications and indicate which of the two conditioning sets seems to be the most appropriate.

The structural model allows for time-variation, and the estimation technique relies solely on the data to gauge the importance of time-variation for each of the mutual funds. Consequently, no choice of window length has to be made. The Kalman filter optimally determines the weights of each of the observations in determining the exposure, given the imposed model structure. Furthermore, the model specification can be tested and confidence bounds on the exposures are readily obtained by applying the Kalman filter. These issues are not straightforward for the traditional techniques.

The structure of the remainder of this paper is as follows. Section 7.2 motivates the use of style analysis. In section 7.3, the model is described and the similarities between the traditional models and the Kalman filter approach are indicated. In Section 7.4, three stylized examples are presented in order to compare our approach with traditional rolling window regressions. Section 7.5 contains empirical applications in which we analyze the investment style of two samples of mutual funds. Finally, Section 7.6 concludes.

7.2 Mutual fund misclassification

The number of mutual funds has increased rapidly over the last decade. Despite the generally poor performance of mutual fund managers, individual investors have increased their demand for investment management; see e.g. Gruber (1996), and Chan, Chen & Lakonishok (2002). The specific needs of investors are reflected by a variety of funds with different investment objectives. For a large part of the funds the fund's name describes its style rather adequately. However, a substantial part of the funds have misleading names, vague investment objectives, or pursue a different style than advertised.

It is not obvious why mutual funds are unclear about their investment policy, since potential investors need detailed fund information to construct an optimal portfolio of mutual funds. Uncertainty about the style of the mutual fund obscures investor's decision and may be a hindrance for them. A possible reason for vagueness in the stated objective of the mutual fund is lawsuit avoidance. While temporary deviations from the style are often observed, the official investment objective is rarely changed. Consequently, the stated objectives of the funds should not be too stringent and possess a certain degree of vagueness. To illustrate this we quote from the 2001 prospectus of the Templeton World Fund. Its main investment objective is stated: *Under normal market conditions, the Fund invests mainly in the equity securities of companies listed anywhere in the world, including emerging markets. At least 65% of its total assets will be invested in issuers located in at least three different countries (including the U.S.).*

Another possible reason for misleading fund names or objectives is to blur the investor's notion of the riskiness of the strategy. Taking on more (undiversifiable) risk usually leads to higher expected returns. Sirri & Tufano (1998) indicate that mutual funds with a high rank in the performance lists of magazines attract more money from the investing public. Apparently, poor performing funds are not punished by massive investor outflows. These results might be an incentive for a mutual fund manager to indulge in more risky asset categories.[3] As DiBartolomeo & Witkowski (1997) phrase it: *The easiest way to win a contest for the largest tomato is to paint a cantaloupe red and hope the judges do not notice.* It is our task to be the judge in this contest and identify the large tomatoes from the painted cantaloupes. In other words, identification of exposures to relevant style or risk factors is of primary importance for investors.

There is ample evidence of the misclassification of mutual funds. For example, both DiBartolomeo & Witkowski (1997) and Brown & Goetzmann (1997) use the realized fund

[3]Alternatively, non-linear assets could be used to game their investment style or performance measures. See for example Lhabitant (2000) and Crowley & Stutzer (2001) for a discussion how mutual fund managers may game their Sharpe ratio or Morningstar rating by including simple option strategies in their portfolio. It is known that identifying non-linear asset structures by applying RBSA is complicated, to say the least; see, e.g., Agarwal & Naik (2000).

returns as inputs for their analysis. Their results suggest that up to 40 percent of mutual funds are in one way or another misclassified. Kim, Shukla & Tomas (2000) report misclassification up to 50 percent when also taking into account other fund attributes (e.g., income ratio, percent stocks) than risk and return measures (e.g., standard deviation, CAPM-beta). These studies do not take into account style changes, or use only a limited amount of data to estimate the investment style of a mutual fund. For instance, DiBartolomeo & Witkowski (1997) and Brown & Goetzmann (1997) take 60 and 24 months, respectively. The importance of incorporating time-variation in style exposures before and after a change in fund manager is investigated by Gallo & Lockwood (1999). They claim that 65 percent of the funds experience a shift in investment exposures after a management change. Brown & Van Harlow (2002) find that mutual funds with low tracking error relative to their style benchmark outperform funds with style drift or high tracking error.

Kuo & Satchell (2001) report that country factors provide more diversification opportunities for investors than industry, size, or value factors. Therefore, we analyze the regional risk exposures of funds with an international equity investment objective. Studies focussing on the performance evaluation of mutual funds with an international investment objective are relatively scarce.[4] According to French & Poterba (1991) and Huberman (2001), investors tend to invest more in stocks they are familiar with. Managers from international investment funds might have the same bias and therefore their funds could be misclassified because they have or had a home bias.

7.3 Determination of the investment style

The RBSA introduced by Sharpe (1992) concentrates on estimating a portfolio that could have been tracked by an investor at relatively low cost. This tracking portfolio is constrained in two ways. First, short sales are prohibited. Second, in order to interpret the exposures as portfolio holdings, their sum should equal one. We follow DeRoon et al. (2003) in their terminology in which they name RBSA subject to both constraints *strong* RBSA. RBSA where both sets of restrictions are relaxed is named *weak* RBSA.[5] An intermediate form with the portfolio restriction but without the short-sales restrictions is labeled *semi-strong* RBSA. We argue later that the short-sale restrictions are in general irrelevant, and should be imposed in certain special cases only. Our empirical examples are based on the semi-strong form of RBSA.

The interest from our style analysis is not the actual *holdings* of a mutual fund, but the *exposures* to certain style categories. This means that a portfolio of US stocks which are

[4]Notable exceptions are Cumby & Glen (1990), Eun, Kolodny & Resnick (1991), Droms & Walker (1994), and Kao, Cheng & Chan (1998).

[5]Alternatively, Agarwal & Naik (2000) label RBSA without restrictions *generalized* RBSA.

also sensitive to the European market results in an exposure towards both these markets. This is relevant information for an investor, since she is now also exposed to risks associated with the European market conditions. So, Sharpe's famous "Duck theorem" applies here: *If it walks like a duck and talks like a duck, for all important purposes, it* is *a duck.*

In weak RBSA, the exposures of the mutual fund are obtained by minimizing the sum of squared errors of the equation

$$R_t^{fund} = \alpha + \beta_1 \cdot R_t^{index1} + \ldots + \beta_K \cdot R_t^{indexK} + \varepsilon_t^{fund}, \quad t = 1, \ldots, T, \tag{7.1}$$

where R_t^{fund} denotes the total return of the fund, and R_t^{indexi} the return on style index i, and ε_t^{fund} the fund specific error terms. The standard assumption that the error terms are independent from the style indices is made. Usually however, two restrictions are imposed. The first restriction is the *portfolio restriction* which requires that the estimations for the parameters β_i can be interpreted as portfolio holdings in style i. This (equality) restriction is

$$\sum_{i=1}^{K} \beta_i = 1. \tag{7.2}$$

The equations (7.1) and (7.2) together are called semi-strong RBSA. A second restriction is the *short-sales restriction*, which imposes that all estimated portfolio holdings should be long positions. These (inequality) restrictions are

$$\beta_i \geq 0, \qquad i = 1, \ldots, K. \tag{7.3}$$

This does not mean that short sales *in general* are prohibited. It states that short sales *in style categories* are not allowed. Strong RBSA is obtained by equation (7.1) together with restrictions (7.2) and (7.3). This is the Sharpe (1992) method of determining a fund's investment style.

Because of the inequality constraints, the coefficients cannot be obtained by applying ordinary least squares (OLS). Quadratic programming (QP) algorithms solve for the exposures $\beta_1, \ldots, \beta_K$. However, as opposed to OLS, confidence regions are not readily obtained when using QP. Attempts to resolve this problem have been made by Lobosco & DiBartolomeo (1997), and Kim, Stone & White (2000), amongst others.

One of the implicit assumptions of the original RBSA is that the exposures stay constant over the sample period. This is highly unlikely in practice. Therefore, rolling regressions are often reported. In this way, the exposures $\beta_1, \ldots, \beta_K$ are not estimated over the entire sample period but over windows (sub-samples). For instance, when a 36-month window is used, the coefficients are estimated over the first three years of the sample. The window moves forward one month, deleting the first observation and adding the observation of the next period. In this way, time-varying exposures are obtained.

However, the use of sub-samples instead of the entire sample means the implicit introduction of time-varying exposures in an ad hoc manner. This approach still assumes that style exposures stay constant over the 36 months estimation period. Implicitly, this creates a contradiction unless the exposure is constant over the entire sample period, and that is exactly the assumption it should relax. Especially in case of a change in fund management the assumption of constant exposures within the 36 months window is restrictive; see Gallo & Lockwood (1999) for a discussion on changing style exposures after management changes. Another shortcoming of a rolling window approach is that estimates rely on historical returns only at each point in time.[6] When the particular application allows this, our approach is able to introduce time-variation by using the return information both before and after that particular period.

We propose an approach different from the traditional rolling window regressions to model time variation in fund exposures, using the *Kalman filter*. First, we explain this method in the weak RBSA form, so without the short sale and portfolio constraint. Time variation is introduced to the model in equation (7.1) by the following set of equations

$$
\begin{aligned}
R_t^{fund} &= \alpha_t + \beta_{1,t} \cdot R_t^{index1} + \ldots + \beta_{K,t} \cdot R_t^{indexK} + \varepsilon_t, && (7.4)\\
\alpha_{t+1} &= \alpha_t, && (7.5)\\
\beta_{i,t+1} &= \beta_{i,t} + \xi_{i,t+1}, && (7.6)
\end{aligned}
$$

for $i = 1, \ldots, K$, and $t = 1, \ldots, T$. Furthermore, the error terms are

$$
\varepsilon_t \sim NID(0, \sigma_\varepsilon^2), \qquad \xi_{j,t} \sim NID(0, \sigma_{j,\xi}^2), \quad j = 0, ..., K
$$

where NID indicates an independent sequence of normally distributed random numbers. The initial conditions for the exposures are (proper) diffuse priors.[7] More specifically, $(\alpha, \beta')' \sim N(0, \kappa \cdot I_{K+1})$, with κ a large but finite number, and I_{K+1}, the identity matrix of dimension $K + 1$. We decide to model the time variation in exposures as in equation (7.6), which states that the exposure in this period is the exposure in the previous period plus a style shock. The exposures $\beta_{i,t}$ are non-stationary in this model. This means that the model allows the exposures to evolve in such a way that fundamental changes in the investment style can be accommodated. The same could be done for the manager ability. However, we have modeled the manager ability in equation (7.5), to be constant over time.

The model presented above is in *state space* form, with equation (7.4) being the *mea-*

[6] See, e.g., the discussion in Belden & Waring (2001) on the disadvantages of the use of historical returns only in a performance measurement context.

[7] As this terminology suggests, the Kalman filter has next to a classical also a Bayesian interpretation.

surement equation, and (7.5) and (7.6) being the *transition* equations. This enables us to directly apply the Kalman filter, which returns the parameters of the model, including the β_t-s. Thus, while the hyper-parameters (σ_ε^2 and σ_ξ^2) are estimated to obtain the model structure, the unobservable exposure coefficients β_t are the variables of interest, since they represent the unknown sensitivity of the mutual fund to the style or risk factor. The variance of the disturbances can be estimated efficiently by using maximum likelihood, while the β_t-s are derived recursively.[8] Model (7.4)–(7.6) is known as the *random walk model*; see Harvey (1993) p. 408.

Models in state space form have been used extensively in engineering. More recently, these models have found their way into econometrics and finance. Extensive treatments of the theory and applications of the Kalman filter in the field of econometrics are Harvey (1993), and Durbin & Koopman (2001), amongst others. Applications modeling time-varying market exposures by the Kalman filter include Alexander, Benson & Eger (1982), Fisher & Kamin (1985), Lockwood & Kadiyala (1988), and Black, Fraser & Power (1992).

The time-invariant weak RBSA regression model can be obtained as a special case of the models presented above which allow for time-variation. When next to the estimates for α also the β_i-s are constant over time, transition equation (7.6) is replaced by

$$\beta_{i,t+1} = \beta_{i,t}.$$

The disturbance term ξ has disappeared (or has zero variance, which is essentially the same).

Modeling the time-varying exposures explicitly leads to (a) a testable model, and (b) efficient use of the data because of the structure that is imposed by the model. The possibility to test the validity of our model assumptions against alternatives makes this technique attractive. Such test can be important, since misspecification may lead to erroneous inferences. When our model is appropriately chosen, the optimal use of the available data is guaranteed by applying the estimation technique we propose. In the empirical section of this paper we test the model with time-variation in exposures relative to a model without and find compelling statistical evidence in favor of a model specification with time-varying exposures. A direct statistical comparison with the results from rolling window regressions is complicated, to say the least. Results from analysis based on either method will be described in the empirical sections of this paper.

In order to incorporate the portfolio restriction (i.e. all exposures sum to one), as is used in the (semi-) strong RBSA literature, in the state space model, the betas should be

[8]We use the Ox-based computer package Ssfpack to evaluate the system. For a detailed description of Ox see Doornik (2001). Ssfpack is described by Koopman, Shephard & Doornik (1999). See www.oxmetrics.com or www.ssfpack.com for more details.

reparameterized. This is a fairly simple operation, and has little impact on the estimation procedure.[9] In accordance with the existing literature on performance evaluation, we incorporate this portfolio restriction by modeling the returns of the mutual funds as well as the returns on the style indices in excess of the risk free rate. This is equivalent to the inclusion of cash as a style index and incorporating the portfolio restriction. Thus, our empirical results are based on semi-strong RBSA. The advantage of this approach is the direct link to asset pricing models like e.g. the arbitrage pricing theory (APT) developed by Ross (1976). The investment styles serve as the risk factors relevant for the potential investor in the mutual fund.

We argue in line with DeRoon et al. (2003) that imposing the non-negativity restrictions is in general not necessary. In fact, using these restrictions may lead to inconsistent parameter estimates when short positions are allowed in practice. For example, a typical growth fund will have a negative exposure for the value (*HML*) factor in the Carhart (1997) model.

An example of an application in which the non-negativity constraints are useful is when the estimated investment style should be replicable for an investor with short-sale constraints. The performance of this constrained investor can be used for comparison with the performance of the mutual fund, given that they have the same (non-negative) style exposures.

In most other applications, the necessity for non-negative exposures is less clear. The use of inappropriate short-sale restrictions may lead to biased or even inconsistent estimates of the exposures. This is clearly at odds with the goal of determining the true underlying investment style of the mutual fund, which is the focus in our paper. When the indices representing the investment styles are inappropriately chosen, e.g. high correlation (or *near-multicollinearity*) or the omission of a relevant asset class, the exposures might become negative even when there is no reason to believe this is the case in reality. We suggest a careful selection of the style indices before applying RBSA. This means that style indices should have low correlation and describe as much as possible from the investment opportunity set of the mutual fund manager.[10]

Furthermore, Agarwal & Naik (2000) suggest omitting the restrictions when applying RBSA to hedge funds. While mutual fund managers are often not allowed to take (large) short positions, this is common practice for hedge fund managers who have almost no limitations in this respect. Applying these models to more dynamic hedge funds is left for

[9] In fact, the K random walks for each β_i are replaced by a series of $K-1$ random walks for the newly defined parameters γ_j, from which the β_i-s are obtained as $\beta_{i,t+1} = \frac{1}{K} + \sum_{j=1}^{K-1} \omega_{i,j}\gamma_{j,t}$, with ω_j representing the weights. For instance, when $K = 3$, the weights are (-1,0), (1,-1), and (0,1).

[10] Like Lobosco & DiBartolomeo (1997) we argue that indices that are highly correlated for a longer period of time are essentially capturing the same style and should be treated as one and the same style.

further research.

7.4 Stylized examples

The performance of the method described in the previous section can be analyzed by stylized examples in which we a priori fix the exposures of the managed fund. This way, a comparison can be made between the estimated exposures by the Kalman filter approach we advocate or the rolling window regressions that are used in many other empirical applications. In this section, we present three examples. These examples are stylized and most likely do not resemble any of the strategies of existing mutual funds. However, these examples might provide more insight in the pros and cons of the different methods when estimating the style exposures of mutual funds. The three artificial funds we present are a fund that radically changes its exposure each decade, a fund that radically changes its exposure each year, and a fund that changes its exposure very slowly. For these three stylized examples, we estimate the random walk model as described by (7.4)–(7.6). We start by describing the stylized examples, and analyze the prediction and explanation quality of the models in the subsections below.

The sample period we use in our example corresponds to the sample period of our empirical applications in the next section, January 1976 to May 2002. The first example is a fund that alternatingly mimics the MSCI USA and the MSCI Europe at the turn of each decade. Over the entire sample period, we assume a tracking error of one percent per month. The deviations from the benchmark are independently and identically and normally distributed. We analyze how this sudden change is reflected in predicted exposures and style estimates by the methods described above.

The second example consists of a mutual fund with highly volatile exposures. The style of this fund is to mimic the MSCI USA in even years and in the MSCI Europe in odd years. Again, we assume a tracking error of one percent as in the previous example. This stylized example shows how the methods behave when investigating a mutual fund with highly volatile exposures.

In the previous two stylized examples the exposures change dramatically at a certain point in time. In the third example, the fund only slowly changes its exposures. It takes three years for this fund to move from a portfolio mimicking the MSCI USA to a portfolio mimicking the MSCI Europe. After three years of increasing European exposure, the reverse change takes place at the same pace. This fund also has a tracking error of one percent per month.

In the two subsections below, we make a distinction between predicting exposures, which can be used for, e.g., risk management purposes, and explaining returns, which can be used for, e.g., performance measurement. The essential difference between predicting

Table 7.1: **Comparison of style prediction methods.** This table contains the mean absolute deviation (MAD) en mean squared deviation (MSD) of the US exposure for the three examples. The first 36 months are used as initialization period, and are not used to compute the distance measures. Reported numbers are averages over 100 simulations.

Panel A: Comparison of exposure estimates for the US.

	Example 1		Example 2		Example 3	
	MAD	MSD	MAD	MSD	MAD	MSD
Rolling window	0.193	0.135	0.521	0.302	0.318	0.131
Kalman filter	0.060	0.033	0.311	0.205	0.152	0.028
Kalman smoother	0.060	0.018	0.255	0.090	0.042	0.004

Panel B: Comparison of predicted mutual fund returns.

	Example 1		Example 2		Example 3	
	MAD	MSD	MAD	MSD	MAD	MSD
Rolling window	1.291	3.759	1.883	6.236	1.380	3.338
Kalman filter	1.069	2.162	1.668	5.592	1.057	1.828
Kalman smoother	0.654	0.701	0.595	0.613	0.622	0.635

and explaining is the set of conditioning information which is used to estimate the exposure at a particular point in time.

7.4.1 Predicting regional exposures

Their is widespread agreement on the benefits of hindsight for prediction purposes. The use of future information could be incorporated either explicitly or implicitly. In this subsection, we carefully mention which information we use in order to make predictions about the future regional exposures of the stylized funds as described above.

The information used to predict the regional exposure of the funds are the returns (in excess of the riskfree rate) on the three regional style indices and the (excess) fund return up to time t. In contrast to other studies, we do not use other conditioning information such as macro variables (see, e.g., Ferson & Schadt (1996)) which may spuriously generate good in-sample predictions. The conditioning information is used to predict the exposures for period $t+1$. The benchmark case is the 36-month rolling window estimator.[11] This method uses information from month $t-35$ to month t in order to predict the exposure for month $t+1$. The estimated exposure over the window is used as an estimator for the future exposure.

In contrast with the empirical examples investigated in the next section, we know the actual exposures of the mutual funds in these stylized examples. We investigate the

[11]We have experimented with rolling windows between 24 and 60 months, but the results are very similar to the 36 months we use throughout this paper.

accuracy of the estimation method by comparing the *predicted* U.S. exposure with the *actual* U.S. exposure. We use two distance measures to evaluate the forecast performance of our model. The first is called the mean absolute deviation (MAD), and the second the mean squared deviation (MSD). The second method puts more weight on large prediction errors. Formally, the criteria are

$$MAD_p = \frac{1}{T}\sum_{t=0}^{T-1}\left|\widehat{\beta}^{US}_{p,t+1} - \beta^{US}_{p,t+1}\right|, \quad (7.7)$$

$$MSD_p = \frac{1}{T}\sum_{t=0}^{T-1}\left|\widehat{\beta}^{US}_{p,t+1} - \beta^{US}_{p,t+1}\right|^2, \quad (7.8)$$

where we let $t = 0$ correspond with the first period with an estimate for the rolling window method.

We compare these measures of forecasting the style of the mutual fund with the different prediction methods. In Table 7.1, Panel A, the MAD and MSD from (7.7) and (7.8) are displayed. As can be seen from the table, the rolling window estimator performs worst regardless of the types of exposure change in the examples. In the first example, the MAD equals 19.3 percent for the rolling window estimator, while the Kalman filter does better with 6.0 percent. This means that the exposure is predicted with only 6.0 percent absolute error, on average. The average style forecast residual is more than three times as large for the rolling window predictor.

Since the second example has highly volatile style changes, the average forecast error of both methods are substantially higher. The MAD-gain from using the Kalman filter in this example is reduced relative to the rolling window estimator, with 31.1 versus 52.1. While the absolute gain is more than 20 percentage points, the relative improvement of 40 percent is a little less than in example one. In the third example, with slow moving style exposures, the Kalman filter predicts the style twice as accurate when using the MAD-measure, and more than four times as accurate when using the MSD-measure.

In the stylized examples, we are able to compare the estimated style exposures with the real exposures. For the empirical examples analyzed below, this is obviously not possible anymore. Therefore, we choose to compare the predicted returns from our style exposures with the actual returns. The predicted returns are defined as the predicted intercept and the predicted style exposures times the actual style returns at $t + 1$. The measures from

(7.7) and (7.8) change to

$$\widehat{MAD}_p = \frac{1}{T}\sum_{t=0}^{T-1}\left|\widehat{\alpha}_{t+1} + X_{t+1}\widehat{\beta}_{p,t+1} - R_{p,t+1}\right|, \tag{7.9}$$

$$\widehat{MSD}_p = \frac{1}{T}\sum_{t=0}^{T-1}\left|\widehat{\alpha}_{t+1} + X_{t+1}\widehat{\beta}_{p,t+1} - R_{p,t+1}\right|^2, \tag{7.10}$$

where it should be noted that $\widehat{\beta}_{p,t+1}$ is the vector with style predictions for time $t+1$. These measures are also calculated for the stylized funds and the results are displayed in Panel B of Table 7.1. A comparison between the Kalman filter and rolling window predictions are again in favor of the former. The relative improvement is largest when the styles change slowly over time. The gain in MAD for the third example is over 20 percent, which is substantially lower than the improvement of 50 percent reported on the basis of the test directly on the style exposure itself. Thus, actual improvements of the style estimates on basis of this derived statistic might be larger than the percentage difference in this derived statistic, where at each point in time each style estimate is weighted by its corresponding style return.

In these stylized examples, where the style exposures are modeled as random walks, the prediction is improved in each of the three circumstances. These examples suggest that using the Kalman filter to forecast exposures is beneficial for applications in mutual fund style analysis.

7.4.2 Describing regional exposures

When the aim of the analysis is a *description* of regional exposures rather than *predicting* future exposures, the conditioning information set increases. Applications for which the inclusion of future information is harmless is performance evaluation conditional on the style. In fact, this is standard practice for performance evaluation studies. The estimation of Jensen's alpha conditional on risk exposures to an asset pricing model, such as Carhart (1997), is frequently used to measure the benefits of investing in the mutual fund. The information used to estimate the risk exposure is based on a regression over the entire sample, using both information from the past as well as the future. Our structural model also uses return information from the future to determine the style, but in contrast to the existing models, it allows these exposures to vary within the estimation sample.

In order to use the entire sample and still introduce time-variation in exposures, we use the Kalman smoother. This basically is the Kalman filter used twice, first forward in time, and when the end of the sample is reached the filter is applied backwards through time. This is the optimal way of using information given the imposed model. When the quality of the filtered style estimates is better than the smoothed estimates, the model might be misspecified. As we will see in the examples discussed below, in the case of jumpy exposures this misspecificiaton can be observed. However, given the slight misspecification (the stylized exposures are not random walks), structural shifts in the exposures can be captured well by our model.

In Figure 7.3, Panel B, we observe that when exposures change smoothly over time, the smoother is able to capture the dynamics accurately. The lines with true exposures and estimated exposures deviate only close to the turning point. Comparing the smoother to the filter, which are both displayed in Panel B, we conclude that the use of the smoother is superior to that of the filter when exposures are varying slowly over time. In Figure 7.1 and 7.2, it become clear that the smoother has more trouble capturing sudden changes in exposure. As expected, Figure 7.1 shows that the exposure already starts increasing a year before the actual change is taking place, because the smoother anticipates the style change by using future information. In Figure 7.2 we see that the smoother has some difficulty capturing the dynamic exposures of the fund. By visual inspection, the accuracy of the smoother seems higher than for the filter or the rolling window estimator. This is supported by more quantitative measures, as can be seen in Table 7.1. In that table, the MAD and MSD are presented between the real exposure and the estimated exposure. The smoother is almost equat to the filter in the first example as far as MAD is concerned, but in both other examples it outperforms the filter and rolling window estimator in capturing the exposures.

Not surprisingly, the use of an expanded information set renders results closer to the true results. Whereas the use of future information is common for performance evaluation with fixed exposures (see Carhart (1997)), it is certainly not standard when time-variation is introduced. One could think of an ad hoc solution to incorporate valuable future information by using the 18 months before and 18 months after a certain period to obtain the 36-months rolling window estimator. However, the same disadvantages that we mentioned in the previous sections apply to this rolling window estimator, and hence we propose the use of the Kalman smoother instead.

The results from this section show that the rolling window approach which is used in many empirical applications can be improved upon when the coefficients are changing over time. The evidence presented in this section is suggestive in the sense that existing style estimates are inaccurate either due to (a) the lack of accounting for time-variation, or (b) an ad hoc method to account for time-variation. In the next section, we apply the techniques introduced in the previous section to real mutual fund exposure prediction and performance attribution.

7.5 Empirical applications with time-varying exposures

In the previous section, we have analyzed the differences between the traditional rolling window estimators and the Kalman filter by three stylized examples. These results suggest that the use of this technique may improve existing results in the mutual fund literature. In this section, we examine two empirical applications of our method. The first empirical example is the regional exposures of a sample of mutual funds with an international or foreign investment objective. The second empirical example analyzes the exposures to the market, value, and size factor of a sample of asset allocating funds, i.e. market timers.[12]

7.5.1 Regional exposures of international mutual funds

In this section, we examine the regional exposures of a sample of mutual funds with an international or foreign investment objective. We start this section by a short description of the data. Next, we apply our technique to the prediction of styles. Finally, we examine the ability of mutual fund managers to change their exposures towards markets with high returns.

Heston & Rouwenhorst (1994) and Kuo & Satchell (2001) report that the largest diversification benefits for investors can be obtained by investing internationally. However, research on international mutual funds is scarce compared to domestic equity funds. While some international funds keep their regional exposures fixed over time, others choose to follow a value weighted international benchmark. In addition, fund managers might be home biased (see e.g. French & Poterba (1991) or Huberman (2001)) and invest disproportionally in domestic stocks. These issues warrant more insight in regional exposures of international mutual funds which motivates our sample selection criterion.

The funds in our sample are based on prior research on U.S. based international mutual funds. We take the funds used in Cumby & Glen (1990) and Eun et al. (1991) with an international or foreign investment objective.[13] We collect our mutual fund data from Morningstar. We have monthly total return data from January 1976 until May 2002.[14] Descriptive statistics on the fund from our sample can be found in Table 7.2. The average returns of the funds range from 0.87 to 1.35 percent per month. The standard deviations of the returns are between 2.75 and 5.18 percent.

[12]Unreported Chow and CUSUMSQ tests indicate that the hypothesis of constant exposures over the entire sample period is rejected for almost all funds in these applications.

[13]Several mutual funds from these papers have changed names; see Table 7.1. The Invesco GT Pacific Fund and Merrill Global Equity Fund are not in our sample because they are not listed in the US anymore. The Kemper International Fund merged into the Scudder International Fund. The Transatlantic Fund is not in the Morningstar database with unknown reason.

[14]The total return data from January 1976 – May 1982 are from the Morningstar Principia March 1995 CD-ROM, while the June 1982 – May 2002 are from the Morningstar Principia Pro Plus for Mutual Funds June 2002.

Table 7.2: **Descriptive statistics mutual funds, June 1982 – May 2002.** The first column contains the name of the fund in May 2002. The American Funds New Perspective Fund was previously named the New Perspective Fund, the Evergreen International Growth Fund was the Keystone International Fund, the First Eagle SoGen Global Fund was the SoGen International, Waddell & Reed Adv International was the United International Growth. The second column displays the share class, which denotes the tax or fee structure of the fund. In the third column we find the the fund's inception date, the fourth the ticker code, and the fifth the prospectus objective. The last two columns contain the average realized total returns, and the standard deviation of the total return. Although we use return data starting in January 1976 in the empirical analysis, the average, and standard deviation are calculated over June 1982 – May 2002 for ease of comparison.

Name	Class	Inception	Ticker	Prospectus object.	Average	Stdev
Alliance International	A	1981-06	ALIFX	Foreign Stock	0.91	5.10
American Funds New Perspective	A	1973-03	ANWPX	World Stock	1.26	3.98
Evergreen International Growth	B	1954-10	EKZBX	Foreign Stock	0.87	4.37
First Eagle SoGen Global	A	1970-04	SGENX	Multi-Asset Global	1.20	2.75
Oppenheimer Global	A	1969-12	OPPAX	World Stock	1.35	5.18
Putnam Global Growth	A	1967-09	PEQUX	World Stock	1.11	4.98
Scudder International	S	1953-06	SCINX	Foreign Stock	1.07	4.62
Templeton Growth	A	1954-11	TEPLX	World Stock	1.24	4.01
Templeton World	A	1978-01	TEMWX	World Stock	1.20	4.12
T. Rowe Price International Stock	A	1980-05	PRITX	Foreign Stock	1.06	4.69
Vanguard International Growth	A	1981-09	VWIGX	Foreign Stock	1.15	4.75
Waddell & Reed Adv International	A	1970-06	UNCGX	Foreign Stock	1.08	4.66

Table 7.3: **Descriptive statistics regional style factors, June 1982 – May 2002.** The average US dollar returns, standard deviations, and correlations of the style factors are presented. The regional indices used are those of Morgan Stanley Capital International (MSCI). The Pacific index is excluding Japan. The average and standard deviation are in percentages
per month.

	Average	St.dev.	Min	Max	Correlation			
USA	1.28	4.42	-21.22	13.28	1.00			
Europe	1.24	4.67	-18.98	11.92	0.63	1.00		
Pacific	0.96	6.52	-43.55	20.76	0.53	0.58	1.00	
Japan	0.94	7.12	-19.38	24.26	0.31	0.50	0.32	1.00

The data on the regional indices are from Morgan Stanley Capital International (MSCI), and contain reinvested dividends. The data on the risk free rate are obtained from the website of Kenneth French. Descriptive statistics of the regional indices can be found in Table 7.3. The US has had the highest average returns and the lowest volatility over the sample period. The lowest monthly return is obtained by the Pacific, which lost more than 40 percent of its value in one month. The sharpest increase within a month is in Japan, almost 25 percent. The correlation between the four indices is in general modest, Europe and the US top the list with just over 63 percent.

The analysis below focuses on the prediction of regional exposures for the mutual funds in our sample. Since the real exposures[15] are not available, we need another measure to check for the quality of our predictions. We measure the difference between the realized return and the predicted return by the rolling window and Kalman filter method. The predicted returns are calculated as the *predicted* exposure times the *realized* return on the benchmark indices. For reasons of brevity we do not provide graphs of the regional exposures for each of the funds in our sample. Instead, we examine only one fund in detail with graphs, the Vanguard International Growth Fund, and provide tabulated results for the remaining funds.

The European exposure of the Vanguard fund increases over the period 1995-2002, as can be seen in Figure 7.4, Panel A. This result is obtained from the rolling window estimator, the filter, the smoother, and holdings information. The exposure to Japan has decreased, most notably during the Asian crisis, from 20 percent to 10 percent. Since this fund is a foreign investment fund, we expect no exposure to the US market. Panel C

[15]The Morningstar data some data on the regional holdings of the mutual funds. However, our analysis focuses on *exposures* rather than *holdings*. While holdings information might also provide insight in the fund's style, known problems such as window dressing (see, e.g., Lakonishok, Shleifer, Thaler & Vishny (1991)) and the use of futures might blur risk measurements based on this information. In Figures 4a-d the holdings are presented next to the exposure estimates.

Table 7.4: **Comparison of style forecasting performance for international mutual funds.** The mean absolute deviation (MAD) and mean squared deviation (MSD) between predictions generated by the 36-month rolling window estimator and the Kalman filter are displayed for our sample of international (world or foreign) mutual funds. Since the actual style exposures are unknown, the MAD and MSD measure the difference between the *predicted* style times the *realized* style return and the *realized* return of the mutual fund. The first 36 months are used as initialization period and not used to measure the differences. The last two columns show the perentage gain obtained when using the Kalman filter relative to the 36 month rolling window estimator. The last row contains averages over our sample.

	Rolling window		Kalman filter		Percentage	
Name	MAD	MSD	MAD	MSD	MAD	MSD
Alliance International	1.75	6.24	1.61	4.84	-7.8	-22.5
American Funds New Perspective	1.11	2.26	1.06	2.07	-4.2	-8.3
Evergreen International Growth	1.60	4.75	1.55	4.35	-3.1	-8.4
First Eagle SoGen Global	1.19	2.34	1.11	2.15	-6.8	-8.3
Oppenheimer Global	2.13	8.43	2.06	8.37	-3.4	-0.7
Putnam Global Growth	1.48	4.72	1.47	4.40	-0.5	-7.0
Scudder International	1.28	2.97	1.21	2.37	-6.0	-20.1
Templeton Growth	1.31	3.34	1.32	3.38	0.3	1.1
Templeton World	1.22	2.50	1.19	2.34	-2.6	-6.3
T. Rowe Price International Stock	1.07	2.15	1.02	1.85	-4.7	-13.7
Vanguard International Growth	1.27	2.97	1.26	2.80	-0.8	-5.5
Waddell & Reed Adv International	1.81	6.16	1.73	5.67	-4.5	-8.0
Total	1.44	4.07	1.38	3.72	-3.7	-9.0

shows that there is a slightly negative exposure over the latter part of the sample. The exposure to the Pacific index is also decreasing from 1995-2002, where the most notable change takes place in 1998, when there was a financial crisis in the Pacific region.

The prediction quality between the filter and the rolling window estimator is analyzed in Table 7.4. In 11 out of the 12 mutual funds from our sample, the predicted returns improve when the Kalman filter is used. A (pairwise) Wilcoxson signed rank test rejects the null hypothesis of equal medians for both methods, with a p-value of 0.002. The average gain in MAD is 3.7 percent, while the average MSD is reduced by 9.0 percent. Thus, while our method statistically improves the style estimates in most cases, the economic magnitude of the improvement is generally not substantial.

We stress that a shift in regional exposures need not be a shift in investment style of the mutual fund. When the fund sticks to its benchmark, for example the MSCI World, the regional exposures change over time due to the changing weights of the regions in the index. Such change in exposure should not be confused with a change in investment style.

It is relevant for potential investors to investigate whether international mutual funds

Table 7.5: **Comparison of correlations between changes in style and style returns.** The correlation between the estimates from the rolling window (and Kalman filter) and the realized return in the same period are used to obtain insight in the additional value provided by the mutual fund by changing the regional exposure. The significance of the estimated correlations is indicated by * and ** for the 90 and 95 percent significance level, respectively.

	Rolling window				Smoother			
Name	USA	EUR	PAC	JAP	USA	EUR	PAC	JAP
Alliance	*0.115	**-0.120	0.088	0.077	0.019	**-0.136	0.000	-0.017
American Funds	-0.013	0.012	-0.017	**0.136	-0.035	0.039	0.000	0.000
Evergreen	0.023	-0.011	-0.034	-0.007	0.005	0.018	0.012	0.055
First Eagle SoGen	-0.004	0.036	-0.031	-0.028	0.021	0.017	0.014	-0.061
Oppenheimer	-0.014	-0.006	-0.061	0.036	-0.041	0.034	0.000	-0.029
Putnam	-0.040	-0.042	-0.030	0.024	*-0.097	0.026	0.004	-0.043
Scudder	0.091	-0.071	0.032	0.078	0.045	-0.015	0.092	-0.027
Templeton Growth	0.005	0.020	0.020	-0.015	0.010	-0.056	0.008	-0.076
Templeton World	0.025	-0.044	0.057	-0.017	0.018	-0.030	-0.029	**-0.124
T. Rowe Price	0.036	**-0.140	-0.023	**0.177	-0.013	-0.004	0.013	0.061
Vanguard	0.050	**-0.174	-0.043	**0.159	0.019	-0.070	0.042	0.034
Waddell & Reed	0.019	-0.028	0.033	*0.110	-0.007	0.030	0.074	0.000

are able to anticipate abnormal high (low) regional returns by increasing (decreasing) their exposure towards these regions. This timing ability can be analyzed by the correlation between the exposure and the returns. A study investigating the regional timing performance of mutual funds requires an accurate description of the regional exposures. Since we are not concerned with prediction in this application, we use the entire data set to estimate the exposure in a certain period. This allows us to use the Kalman smoother instead of the Kalman filter. The use of this future information is in similar spirit to the current literature on mutual fund manager ability; see Carhart (1997) amongst others. Nevertheless, when time variation of exposures is allowed the use of rolling window estimators (which do not use future information) is common practice.

The correlation analysis is displayed in Table 7.5. The table shows that inference on regional timing is influenced by different style estimation methods. In particular, the significant positive timing for Japan in the rolling window estimator for American Funds, T. Rowe Price, Vanguard, and Waddell & Reed is not found when the Kalman smoother is used. On the other hand, the significant negative timing for Europe for T. Rowe Price and Vanguard also vanish when the smoothed analysis is used. Hence, the method used to calculate timing ability has an impact on the final results on timing. A more detailed analysis investigating regional timing is beyond the scope of this paper.

The Jensen's alphas of the funds are in Table 7.6. Averaging the rolling window alpha

Table 7.6: **Comparison of selectivity coefficent (alpha) for international mutual funds.** The average value alpha from the rolling window estimator are used to measure the selectivity or micro-forecasting skills of the mutual fund manager. The standard errors are computed using the Newey-West correction for autocorrelation. The smoothed alphas with t-values are displayed in the last two columns. The last row contains the average over our sample of funds.

	Rolling window		Kalman smoother	
Name	Alpha	t-val	Alpha	t-val
Alliance	-3.33	-3.68	-1.32	-0.89
American Funds	1.38	1.15	2.48	2.62
Evergreen	-3.60	-2.68	-2.48	-1.86
First Eagle SoGen	2.56	2.49	3.59	3.84
Oppenheimer	1.48	0.60	3.37	1.90
Putnam	-0.22	-0.36	-0.29	-0.22
Scudder	-1.09	-1.75	-0.99	-1.04
Templeton Growth	1.42	1.29	3.18	2.67
Templeton World	0.57	0.65	1.48	1.34
T. Rowe Price	-1.49	-2.18	-0.85	-0.93
Vanguard	-0.35	-0.79	0.09	0.07
Waddell & Reed	-1.06	-0.83	-0.62	-0.47
Total	-0.31		0.64	

estimates results in a negative alpha of 31 basis points per annum. For eleven out of twelve funds in our sample, the Jensen's alpha measure is higher when analyzed by the structural model and estimated by the Kalman smoother. A (pairwise) Wilcoxson signed rank test rejects the null hypothesis with a p-value below 0.001, indicating that the median alpha of the Kalman smoother is significantly larger than that of the rolling window estimator. The economic differences between the alphas are modest in magnitude. Nevertheless, our results indicate that the relative performance for international mutual funds is positive rather than negative, as is indicated by the rolling window estimators.[16]

7.5.2 Three-factor exposures for asset allocators

The time-variation in exposures for the funds in the previous section is not obvious. The funds in this section explicitly state in their objectives that they are changing their exposure to risk factors, such as the market. We investigate whether the exposures to the risk factors in Fama & French (1993) can be predicted by the Kalman filter method. This is done, as in the previous section, by investigating the difference between the actual fund

[16]This statement holds for our sample of funds, and not for international mutual funds in general, because we have ignored the potential survivorship bias. In any case, we expect the influence of survivorship bias to be low, since most of the funds used in studies in the early 90-s still exist.

return and the predicted factor exposures times the realized factor returns.

We select the mutual funds with an asset allocation objective and inception date before 1995. This sample consists of 87 mutual funds. The sample period ranges from June 1982 until May 2002. For reasons of brevity, we do not report results for each of the funds separately. Figure 7.5 contains the sorted percentage improvement of the MAD measure for the sample of funds. The figure shows that for this type of funds, the reduction in MAD is more than 5 percent for half of the sample. For 66 out of 87 cases, our method is an improvement over the rolling window predictor. A (pairwise) Wilcoxson signed rank test rejects the null hypothesis of equal medians for both methods, with a p-value below 0.001. Even in the worst case, the Kalman filter method is just 7.4 percent worse than the rolling window, while 24 funds account for an improvement larger than 7.4 percent when using the Kalman filter. The average reduction is 4.7 percent for the MAD, while it is 9.6 percent for the MSD. Improvements for the latter measure are as large as 42 percent, while in the worst case, only an 18 percent loss is observed. These results indicate that for prediction purposes, the use of the random walk model can improve the style or risk exposures of mutual funds.

7.6 Conclusions

Return-based style analysis is a useful, generic, and quickly applicable tool for investors to get a first impression about the investment philosophy of a mutual fund or the family it belongs to. In addition, the results from style analysis are often used for performance measurement. There is ample evidence that the investment style of managed funds is time-varying, which complicates the style estimation in a standard regression framework. Often, time-varying exposures are incorporated implicitly by using rolling window estimators. The length of this window is generally chosen ad hoc and not motivated by statistical theory. Moreover, the assumption that styles are constant within each of the estimation windows is inconsistent by itself, unless the style is constant over the entire sample period. We introduce an alternative statistical model and estimation technique which alleviates these problems while explicitly incorporating style changes, and does not depend on arbitrarily chosen window sizes.

In this paper, the Kalman filter approach is used to explicitly model time variation of exposures for return-based style analysis. In contrast with rolling window regressions, the entire sample period can be used to obtain efficient estimates of the exposures at each point in time by the Kalman smoother. In addition, these style estimates change smoothly over time, reducing the influence of spurious correlation between style indices and mutual fund returns in small samples. We present three stylized examples in order to demonstrate the huge differences that may be obtained by rolling window regressions instead of the

Kalman filter approach. From these stylized examples it follows that the Kalman filter and smoother are much closer to the true underlying investment style than the rolling window alternative.

The statistical model we advocate in this paper is applied on two sets of mutual funds. First, the regional exposure of a sample of US-based international mutual funds are analyzed. Since the exposures to style factors are unobservable, we analyze their use in predicting the mutual fund returns. Our results indicate that for 11 out of 12 funds the *return predictions* are better by using our method, albeit a modest improvement only. Due to the unobservability of the actual style exposures, we cannot infer the increased level of precision of the *style predictions*. Our stylized examples suggest that the improvements in the style exposures might be substantially higher. We also report differences in inference when timing ability is measured using rolling window estimators and the Kalman smoother. Finally, whereas the rolling window analysis suggests that the mutual funds from our sample exhibit a negative performance relative to their style benchmark, the Kalman smoother approach finds weak evidence for positive selectivity performance.

Second, we also apply our method to a sample of asset allocators, which have the change of exposures as a stated objective in their prospectus. We find that our method improves style predictions for 66 out of 87 funds. Even the worst case increases the mean absolute deviation by only 7.4 percent. A reduction in MAD larger than 7.4 percent is obtained for 24 of the mutual funds.

The empirical results suggests that, in addition to the statistical justification, our model is also of practical use. However, it is clear that this is not a cure-all, the magnitude of the improvements obtained are modest and can be seen as a refinement on current practices.

Figure 7.1: **Exposure to the U.S. for Example 1.** In Panel A, the predicted exposures by using the 36-month rolling window (circles) and the Kalman filter (squares) are displayed. The true exposure is depicted for ease of reference. The true exposure alternates each decade between 100 percent US and 100 percent Europe. Panel B contains the Kalman filter (squares) and Kalman smoother (triangles), together with the true exposure. The estimation is performed over the full sample (January 1976 – May 2002), but in this figure subsamples are shown for reasons of clarity.

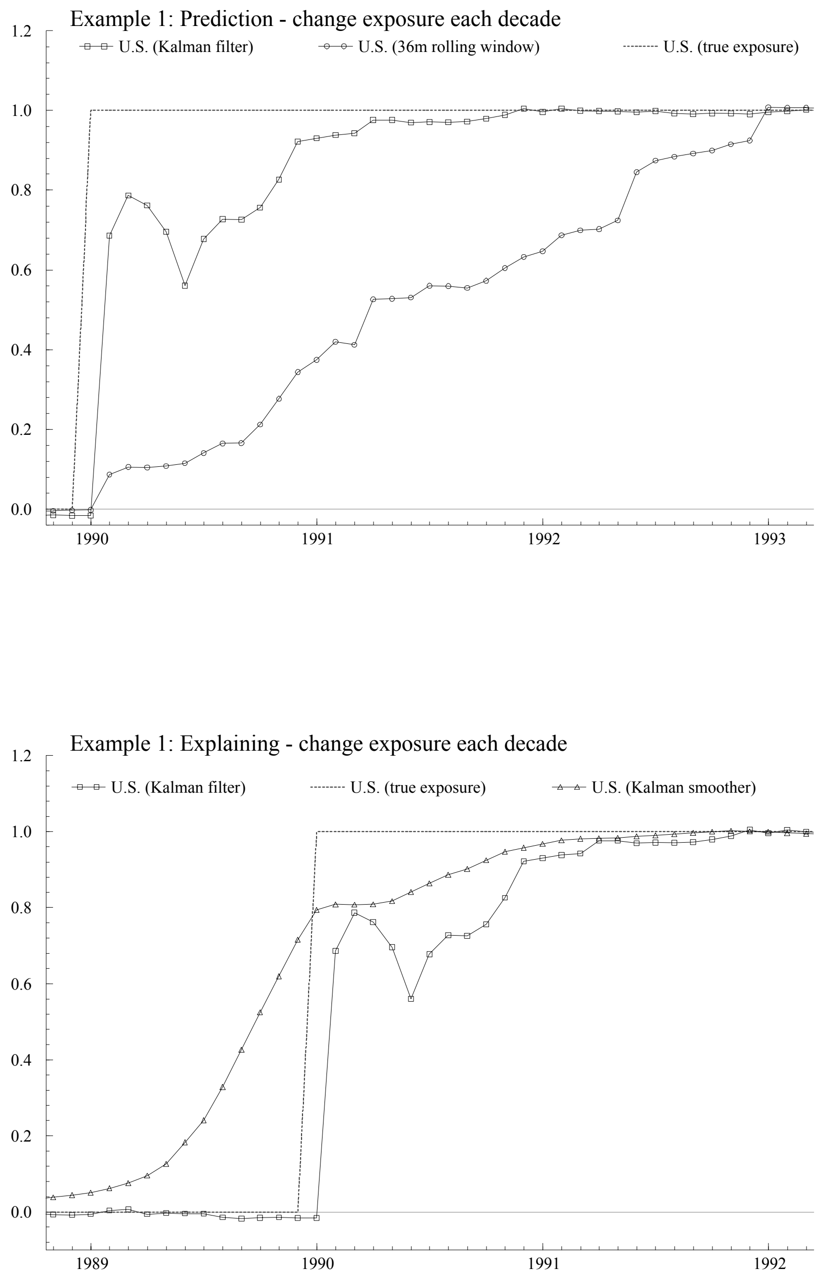
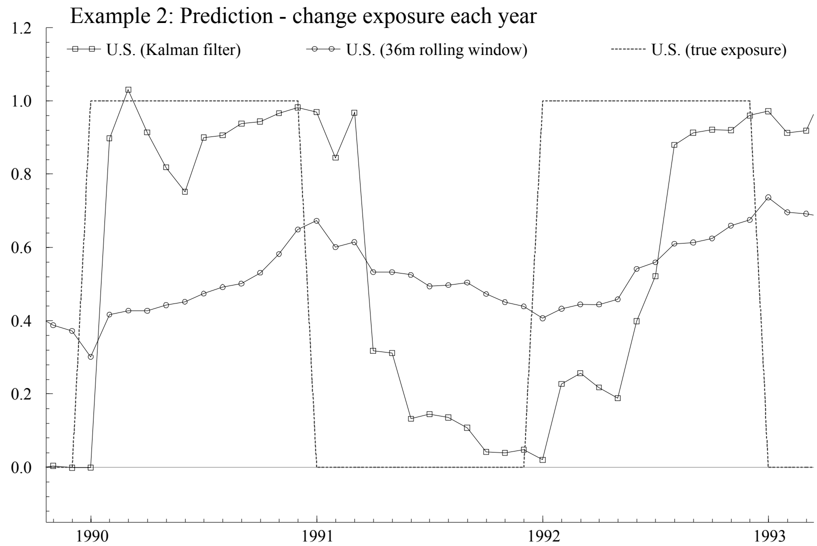


Figure 7.2: **Exposure to the U.S. for Example 2.** In Panel A, the predicted exposures by using the 36-month rolling window (circles) and the Kalman filter (squares) are displayed. The true exposure is depicted for ease of reference. The true exposure alternates each year between 100 percent US and 100 percent Europe. Panel B contains the Kalman filter (squares) and Kalman smoother (triangles), together with the true exposure. The estimation is performed over the full sample (January 1976 – May 2002), but in this figure subsamples are shown for reasons of clarity.



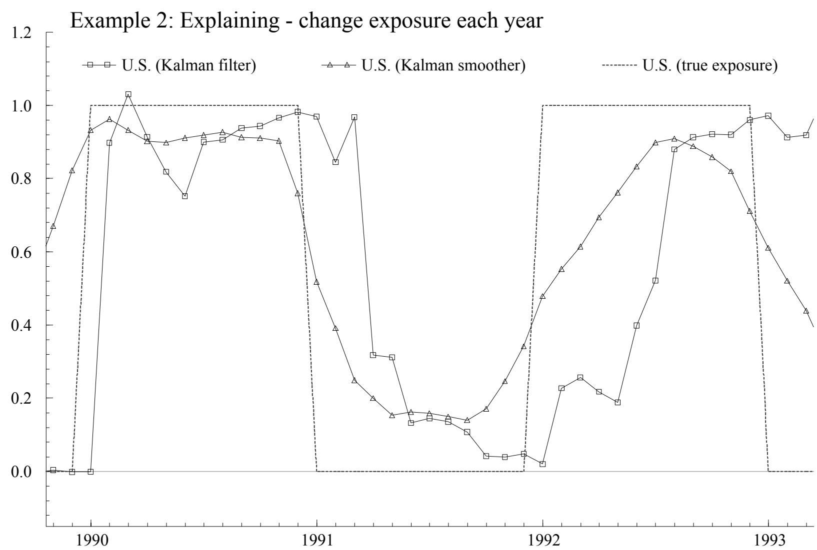
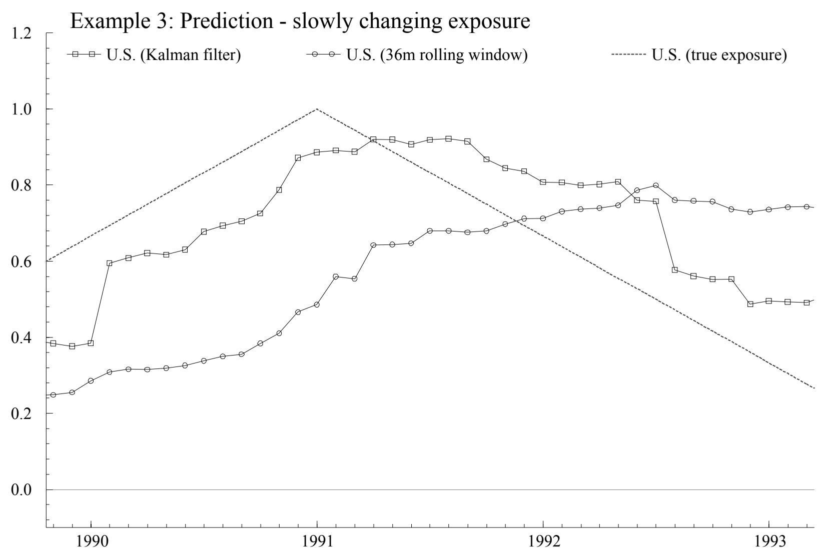


Figure 7.3: **Exposure to the U.S. for Example 3.** In Panel A, the predicted exposures by using the 36-month rolling window (circles) and the Kalman filter (squares) are displayed. The true exposure is depicted for ease of reference. The true exposure slowly alternates 100 percent US and 100 percent Europe. It takes three years for a fully invested position in one region is exchanged for the other. Panel B contains the Kalman filter (squares) and Kalman smoother (triangles), together with the true exposure. The estimation is performed over the full sample (January 1976 – May 2002), but in this figure subsamples are shown for reasons of clarity.



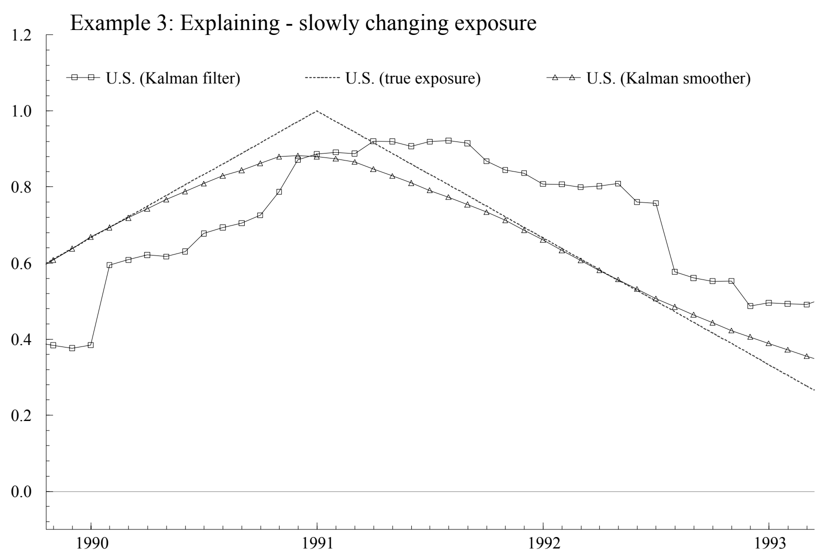
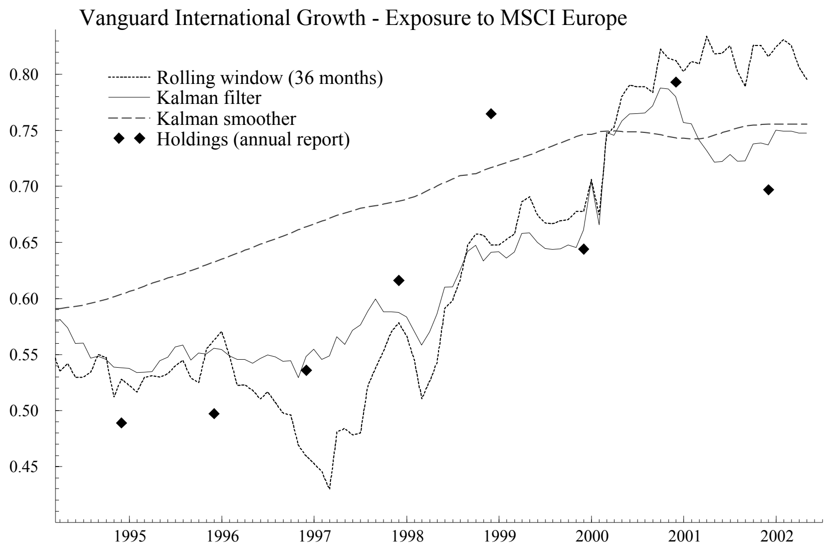
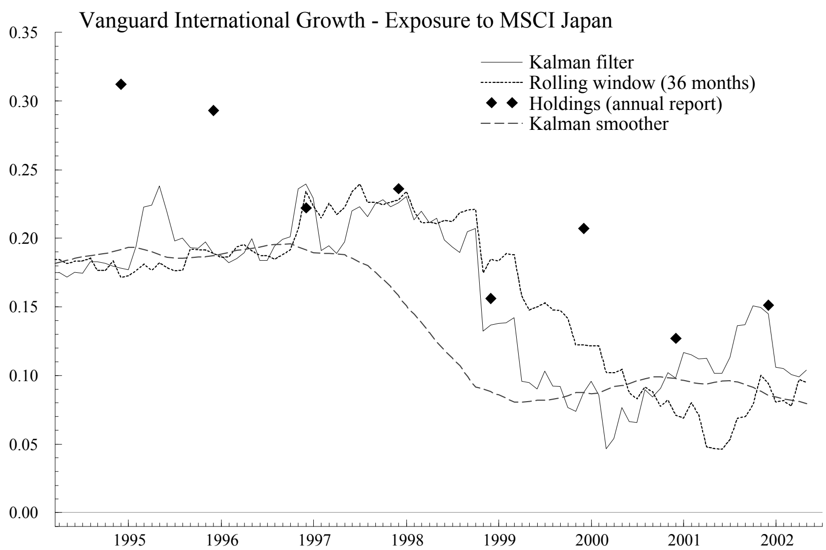
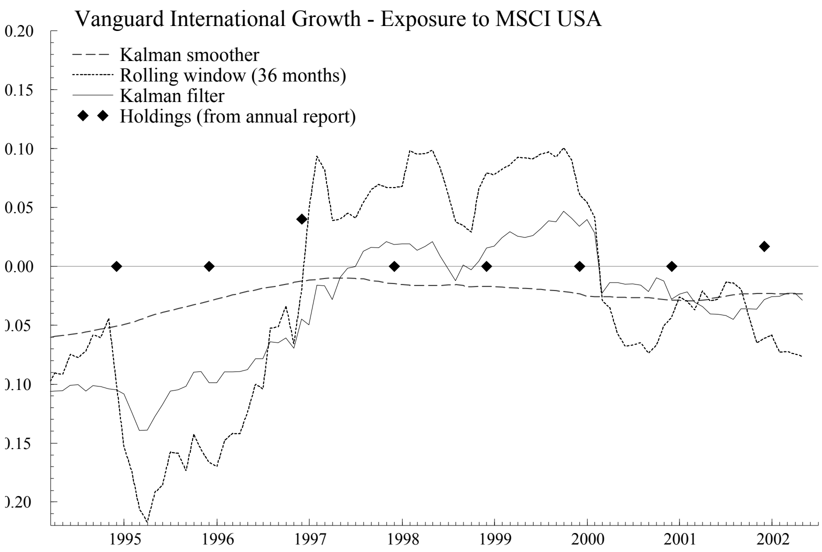


Figure 7.4: **Exposures for the Vanguard International Growth Fund.** The four panels of this table display the exposures to the MSCI Europe, MSCI Japan, MSCI US, and MSCI Pacific excluding Japan. In panels A–D the exposure estimates from the traditional 36-month rolling window, the Kalman filter, the Kalman smoother are presented. The diamonds indicated the holdings fromt the annual reports. The estimation is performed over the full sample (January 1976 – May 2002), but in this figure subsamples are shown for reasons of clarity.






Vanguard International Growth - Exposure to MSCI USA
Kalman smoother
Rolling window (36 months)
Kalman filter
Holdings (from annual report)
0.20
0.15
0.10
0.05
0.00
).05
).10
).15
).20
1995
1996
1997
1998
1999
2000
2001
2002

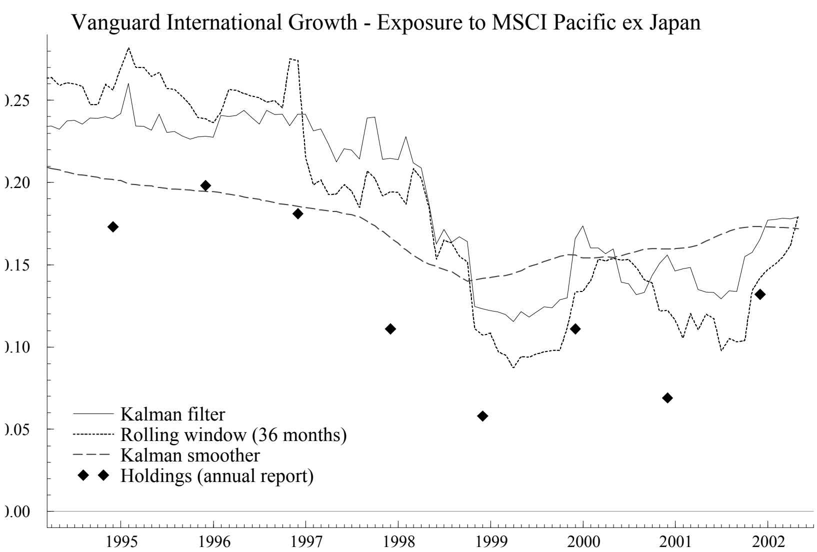
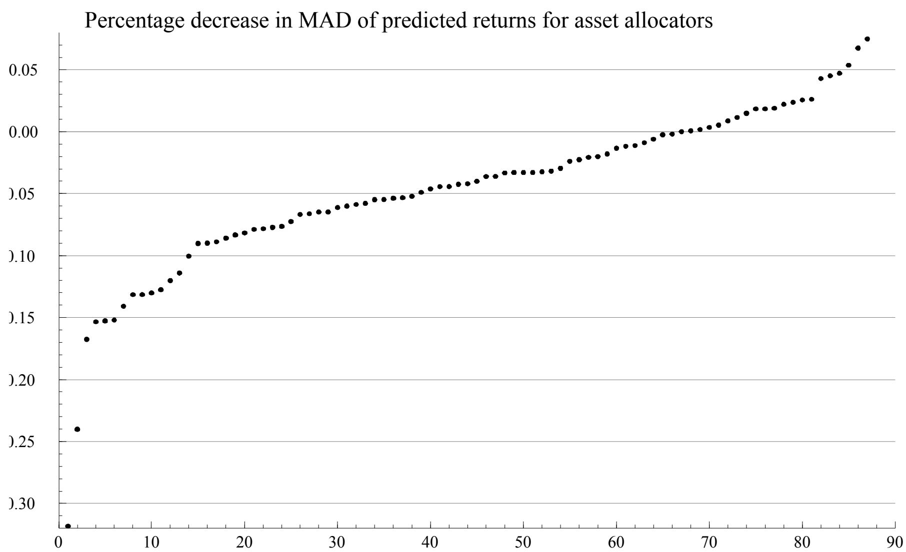

Vanguard International Growth - Exposure to MSCI Pacific ex Japan
).25
).20
).15
).10
).05
).00
Kalman filter
Rolling window (36 months)
Kalman smoother
Holdings (annual report)
1995
1996
1997
1998
1999
2000
2001
2002

Figure 7.5: **Improvements from estimating three-factor model for asset allocators.** This table contains the 87 asset allocation funds, sorted on the percentage gain of the mean absolute deviation (MAD) between the *predicted* fund return and the *realized* fund return. The predicted fund return is the *forecasted* style exposure mulitplied by the *realized* factor return. The horizontal grid starts at a 5 percent loss in prediction accuracy at the top of the figure, and goes down to a 30 percent gain in prediction accuracy for the funds on the left on the horizontal axis.



Chapter 8

Market timing: A decomposition of mutual fund returns

8.1 Introduction

The investment performance of mutual funds is often measured by their average return over a certain holding period. Although these average returns can be quite disperse, it is not always clear what causes these return differences. The dispersion in the average fund return is frequently attributed to the management's selectivity skill (alpha) or the exposure to the stock market (beta). Whereas the alpha is the additional return provided by the fund management, the return differences caused by beta are interpreted as a compensation for bearing undiversifiable risk instead of management skill. Each private investor can decide for himself whether to hedge this market risk and be exposed to the fund's residual return, provided that he has an accurate estimate of the fund's future market exposure. Obtaining an accurate estimate is in general not an easy task, especially when funds exhibit time-varying market exposures.

There is ample empirical evidence that the market exposures of mutual funds change over time; see e.g. Alexander et al. (1982). While this time-variation might be due to beta changes in the fund's underlying stocks, the management might also actively decide to alter the exposure to the market. These active decisions motivated by the suggested ability to predict the direction of the market are often referred to as timing decisions. While investors may benefit from active allocation towards rising and away from declining markets, most of the empirical evidence suggests that mutual fund managers are not capable to adjust their exposures accordingly; see, e.g., Ferson & Schadt (1996).[1]

[1]Other references supporting their findings are, for example, Treynor & Mazuy (1966), Henriksson & Merton (1981), Veit & Cheney (1982), Lockwood & Kadiyala (1988), and Chan & Chen (1992). A notable exception is Bollen & Busse (2001), who find empirical evidence supporting daily timing ability of fund

Funds most prone to actively change their market exposures are the so-called asset allocation mutual funds. These funds claim in one way or another that they move in and out of the stock market when they deem it necessary.[2] The fund's prospectus is often opaque concerning the level of variability in the stock market exposure and the past success of the management in picking bull or bear markets. For a prospective investor's optimal portfolio choice, both the amount of undiversifiable market risk as well as the fund specific component are important ingredients. Knowledge about the dynamics of the fund's market exposure and the associated additional expected return are important for the investor's risk-return trade-off. Conditioning on the current state of the economy and the fund's past behavior may help the investor in deciding whether a mutual fund improves the risk-return trade-off with respect to his existing portfolio.

The mutual fund manager may change the fund's market exposure for a variety of reasons. For example, there is a large literature on the predictability of market returns using publicly available information such as the aggregate dividend yield and measures of the term structure of interest rates. The manager might change his market exposure depending on this publicly available market forecast or on his own interpretation of economic variables. Further, market exposure is adjusted due to the manager's personal expectation about future market movements. We specify a dynamic model for beta to allow for the possibility that fund managers slowly adjust their exposure (e.g. to reduce transactions costs) or have a long-run target beta from which they do no want to deviate too much. Finally, betas may fluctuate randomly, not related to any of the previous components. The skill of the manager can be divided in a selectivity and timing component. If the manager possesses timing ability, the expected conditional return of the mutual fund is larger in periods when the conditional volatility of the stock market is high. Selectivity or alpha captures the systematic fund returns that cannot be explained by the dynamic exposure to the stock market.

The main contribution of this chapter is the decomposition of the mutual fund's conditional expected return in five components; the fund's long-run average market exposure, its reaction on the current macro economic situation, the fund's market exposure in the recent past, market timing, and selectivity (or alpha). This decomposition follows from our specification how a mutual fund changes its market exposure over time. We determine the magnitudes of the components by investigating a representative sample of 78 mutual funds that classify themselves as having an asset allocation perspective. The re-

managers. In addition, Wermers (2000) finds timing ability using a holdings-based performance analysis.

[2]Consider for example the prospectus of the Caldwell and Orkin Market Opportunity Fund, "*The fund normally invests between 90% and 100% in equities; management may modify this allocation range when market conditions warrant.*" or the Gabelli Mathers Fund, "*The fund usually invests a substantial portion in common stocks; it may, however, invest all or any portion of assets in fixed income securities.*"

sults of this empirical analysis shed light on the driving factors behind the conditional and unconditional expected fund return. In order to decompose the fund's conditional expected return, we estimate a dynamic performance evaluation model that generalizes the stochastic market exposure model by Lockwood & Kadiyala (1988) and the conditional performance evaluation model by Ferson & Schadt (1996). The results from our generalized model indicate that for several funds the findings reported in the previous literature might be biased because of a too restricted model specification.

Our empirical results indicate that managers are changing their market exposure substantially over time. The empirical decomposition suggests that management skill, selectivity and expert timing, explain part of the dispersion in cross-sectional fund returns. Our evidence suggests that several funds have significant selectivity and timing skills. We also find that selectivity and timing are negatively correlated, so that investors who pick a fund with high selectivity are likely to end up with negative timing skill. This is important for the portfolio choice problem of individual investors.

We further investigate the relation of turnover and expense ratios with fund performance. The relation with turnover allows us to examine whether heavy trading is associated with higher performance. Our results indicate that the 10 funds with highest and lowest turnover outperform the average fund. Our results suggest that both managers with heavy trading, as well as managers with little trading outperform the average fund. In addition, we find that funds with both high and low expense ratios have managers with better skills than the average fund.

The remainder of this chapter is organized as follows. In Section 8.2 we explain the decomposition of the conditional expected fund return in five factors. In Section 8.3 we describe our sample and how the public market forecast is determined. Section 8.4 analyzes the empirical return decomposition, and is divided in four parts. First, we investigate management selectivity and timing skill. Second and third, we examine the dynamic market exposure and the variability in the fund returns. Fourth and last, we relate our estimation results to other well-known performance evaluation models. In Section 8.5 we investigate the relation between turnover and expense ratios to managerial skill. Section 8.6 concludes the chapter.

8.2 Factors driving the expected fund return

In this section, we decompose the conditional expected market return into five components. This decomposition builds on the large body of literature on return-based performance evaluation.[3] Estimation of these components provides new insights in the importance of the dynamics of a fund's stock market exposure on its average return. The return of a mutual fund is represented by a single factor model, where the (excess) market return is the factor,

$$R^e_{i,t} = \alpha_i + \beta_{i,t} R^e_{m,t} + \varepsilon_{i,t}, \tag{8.1}$$

where $R^e_{i,t}$ denotes the return of the mutual fund i in excess of the risk-free rate in period t, and $R^e_{m,t}$ denotes the excess return of the market over the risk-free rate in the same period. We define . The parameter

$$\beta_{i,t} = \frac{\mathrm{Cov}_{t-1}\{R^e_{i,t}, R^e_{m,t}\}}{\mathrm{Var}_{t-1}\{R^e_{m,t}\}}$$

measures the sensitivity of the fund return to the stock market movement in period t, and $\mu_{i,t} = \alpha_i + \varepsilon_{i,t}$ denotes the unexplained part of the fund's period t return. We assume that the conditional expectation of this unexplained part is time invariant, that is

$$\mathrm{E}_{t-1}\{\mu_{i,t}\} = \alpha_i. \tag{8.2}$$

The intuition behind this restriction is that an asset allocation mutual fund is assumed to have a constant level of selectivity, regardless of the economic situation.[4]

Time variation in the exposure to the stock market is allowed, since asset allocation funds are explicitly aiming to achieve superior returns by increasing (decreasing) their exposure to the stock market when the excess market returns are expected to be positive (negative). The dynamic process for the market exposure is described by

$$\beta_{i,t+1} = \overline{\beta}_i + \rho_i \left(\beta_{i,t} - \overline{\beta}_i\right) + \delta_i' X_t + \tau_i \left(R^e_{m,t+1} - \mathrm{E}_t\{R^e_{m,t+1}\}\right) + \eta_{i,t+1}, \tag{8.3}$$

where $\overline{\beta}_i$ is the long-run average market exposure of fund i, ρ_i is the strength of the delayed reaction (mean-reversion) in the market exposure, $\delta_i' X_t$ captures the manager's reaction to recent macro economic news, τ_i is the market timing coefficient, and $\eta_{i,t+1}$ is the idiosyncratic component not captured by the previous components. Note that for the long-run average to be well-defined the mean-reversion coefficient ρ_i is required to be smaller than one in absolute value. The macro economic series X_t are assumed to be stationary as well (which can be obtained by differencing the non-stationary macro

[3] When the exact portfolio holdings of a mutual fund are known, holdings-based decompositions might be used. See, e.g., Wermers (2000) for a decomposition of mutual fund returns in stock picking talent, style, transactions costs, and expenses.

[4] See, e.g., Christopherson, Ferson & Glasmann (1998) and Christopherson, Ferson & Turner (1999) for a model in which selectivity depends on the recent macro economic developments. Our methodology can be extended in a straightforward way to incorporate this as well.

variables, if necessary).

The expected excess return conditional on public information is denoted by $\mathrm{E}_t\{R^e_{i,t+1}\}$, and equals

$$\mathrm{E}_t\{R^e_{i,t+1}\} = \mathrm{E}_t\{\mu_{i,t+1}\} + \mathrm{E}_t\{\beta_{i,t+1}\} \cdot \mathrm{E}_t\{R^e_{m,t+1}\} + \mathrm{Cov}_t\{\beta_{i,t+1}, R^e_{m,t+1}\}. \tag{8.4}$$

Our aim is to find the driving factors behind the conditional expected return of mutual funds. In order to achieve this goal, the decomposition from equation (8.4) is analyzed using the dynamic process for the market exposure from equation (8.3). The first term, capturing selectivity of the management, is assumed to be constant over time. In order to analyze the second term in the decomposition, the conditional expected market exposure is required. Conditioning on macro economic information and past market exposure we obtain the conditional market exposure for fund i for period $t+1$,

$$\mathrm{E}_t\{\beta_{i,t+1}\} = \overline{\beta}_i + \rho_i \left(\beta_{i,t} - \overline{\beta}_i\right) + \delta_i' X_t. \tag{8.5}$$

This enables us to predict the market exposure in the next period, given the information at the end of this period. The timing component vanishes from equation (8.5), because conditional on the current macro information the market surprise return equals zero. In other words, private investors are assumed to have no market timing ability, so they cannot foresee how the manager is going to change his beta using his private information about future market movements.

The last term from the decomposition in equation (8.4) measures the conditional covariance between the future market exposure of the fund and the future market return. Using (8.3), this component can be straightforwardly rewritten as

$$\mathrm{Cov}_t\{\beta_{i,t+1}, R^e_{m,t+1}\} = \tau_i \mathrm{Var}_t\{R^e_{m,t+1}\}. \tag{8.6}$$

The only fund specific component in this last term is the timing coefficient τ_i. Given τ_i, the conditional variance of the market return determines the conditional expected return from the timing ability of the fund manager. Hence, in tranquil stock markets, the expected return due to timing ability is smaller than in volatile markets. This is consistent with the findings of Pesaran & Timmermann (1995), who conclude that aggregate stock return predictability is lower in calm stock markets.

Over the past decades, many papers have been published on the predictability of the direction of the stock market as a whole.[5] While the evidence in favor of economic predictability is limited, there is some agreement on the predictive power of certain macro

[5]See, e.g., Breen, Glosten & Jagannathan (1989) and Pesaran & Timmermann (1995).

economic indicators. The model for the dynamics in the market exposure in (8.3) investigates the ability of the fund manager to predict the direction of the market in excess of the predicted market return based on publicly available information. In order to separate this notion from usual timing, we use "expert" timing ability to refer to our definition. The intuition behind this expert timing is that private investors may be able to react themselves on the publicly availably macro data in order to time the market by the means of trading a stock index and money market fund. One might expect an asset allocation mutual fund to provide additional value for the private investor on top of the (publicly) anticipated market return. The conditional forecast of the stock market return in excess of the risk-free rate is assumed to be given by

$$\mathrm{E}_t\{R^e_{m,t+1}\} = \gamma' X_t, \tag{8.7}$$

where $R^e_{m,t+1}$ is the return on the relevant stock market index in excess of the risk-free rate in period $t+1$ and X_t is a vector of publicly available information (including a constant) at the end of period t such as (functions of) the dividend yield or measures of the term or credit spread.

The model for the market exposure presented in equation (8.3) reduces to two well-established mutual fund performance evaluation models when appropriate restrictions are imposed. The conditional model by Ferson & Schadt (1996) is obtained when $\rho_i = 0$ and $\eta_{i,t} = 0$ for each t. The stochastic components model by Lockwood & Kadiyala (1988) requires restrictions $\rho_i = 0$ and $\delta_i = 0$. Both models specify the timing component as the cash-versus-stocks decision, instead of relative to the predicted stock market return as in our model. Evidently, when the historical average is used as a predictor in our model, and the necessary restrictions are imposed, our model produces the same results as the models by Ferson & Schadt (1996) and Lockwood & Kadiyala (1988).

Substituting equations (8.2), (8.5), (8.6), and (8.7) into equation (8.3), we obtain the conditional expected mutual fund return,

$$\mathrm{E}_t\{R^e_{i,t+1}\} = \alpha_i + \left(\overline{\beta}_i + \rho_i\left(\beta_{i,t} - \overline{\beta}_i\right) + \delta_i' X_t\right) \cdot \gamma' X_t + \tau_i \mathrm{Var}_t\{R^e_{m,t+1}\}, \tag{8.8}$$

which consists of five different components. Before moving to the empirical implementation, let us consider a stylized example to illustrate the potential magnitudes of the components distinguished above. Suppose that the fund specific parameters are $\alpha_i = 0.05\%$ per month, $\overline{\beta}_i = 0.50, \rho_i = 0, \delta_i = 0$, and $\tau_i = 0.10$. Suppose further that the conditional expected market return for next month is 1.0 percent and the conditional variance is 0.0030 (which corresponds to standard deviation of about 5.5 percent per month). The conditional expected return of this fund now equals

$$\begin{aligned}
\mathrm{E}_t\{R^e_{i,t+1}\} &= 0.05\% + 0.50 * 1\% + 0.10 * 0.30\% \\
&= 0.05\% + 0.50\% + 0.03\% = 0.58\%.
\end{aligned}$$

In this example, the most important factor in the expected return is the average market exposure. The manager skills cumulate to an annual return of 96 basis points (bp). Thus, the private investor (without these skills) would earn almost one percent per year less on his portfolio with the same average beta. Now suppose that the market exposure in the previous period was 0.70, for the mean-reversion parameter we assume $\rho_i = 0.30$, and the macro factors account for $\delta_i' X_t = 0.10$. In this case the return of the fund can be split up in five parts,

$$\begin{aligned}
\mathrm{E}_t\{R^e_{i,t+1}\} &= 0.05\% + (0.50 + 0.30 \cdot 0.20 + 0.10) * 1\% + 0.10 * 0.30\% \\
&= 0.05\% + (0.50\% + 0.06\% + 0.10\%) + 0.03\% = 0.74\%.
\end{aligned}$$

In this second example, the conditional expected return of the fund has increased by 16 bp per month, and we are able to separate how much of the conditional market exposure is due to the long-run average, mean-reversion, and the macro economic situation. Although the conditional expected return increased, the manager skill is the same. Omitting these two additional terms in empirical analyses might bias the estimates found for selectivity and timing. In the next section we estimate the parameters of this model for a sample of asset allocation mutual funds.

8.3 Data

Our focus lies on the performance measurement of mutual funds that try to time the market. Because of their investment philosophy, this group of funds is expected to actively change their market exposure. We analyze the group of funds that classify themselves to the Morningstar database as having an asset allocation perspective.[6] It is required that the fund's inception date is prior to March 1995 in order to have sufficient data available. We excluded 9 funds that are categorized by Morningstar as bond funds, and do not allow multiple share classes of the same fund to be in the sample (so our sample consists of distinct portfolios only). This results in a sample of 78 mutual funds with monthly total return data from June 1972 to May 2002 for the funds that exist over this entire 30-year

[6]This sample selection criterion is similar to Becker, Ferson, Myers & Schill (1999). We do not investigate the possibility of timing between bonds and cash, which might be an alternative way to provide value to the investor.

period. The data for the risk factors and conditioning information are from the data library of Kenneth French and the Federal Reserve Bank of St Louis.

In Table 8.1 we present the summary statistics of the 78 funds in our sample. The average returns from these funds vary between 0.12 and 1.35 percent per month over the period March 1995 to May 2002. The volatility, measured by the standard deviation of the returns over the same period, is between 0.011 and 0.104 percent per month. This large difference in volatility is an indication that some funds invest substantially more in fixed-income type securities than others.[7]

The time-series average of the fund's turnover and expense ratio can also be found in Table 8.1. This data is also extracted from the Morningstar database. We observe that the average turnover also varies substantially across funds. Some funds trade frequently, replacing each asset on average once per quarter. The average expense ratios range from zero to almost 2.5 percent per annum. Below, we relate both turnover and expenses to the fund's performance.

In order to identify expert timing, which is the ability of the manager to anticipate deviations of the market return from the forecast based on publicly available information, we specify a linear forecasting process for the latter. To keep in line with the conditional performance literature, we adopt the predictive variables from Ferson & Schadt (1996). These are (1) the one-month Treasury bill yield, (2) the dividend yield,[8] (3) the slope of the term structure, (4) the quality spread in the corporate bond market, and (5) a January dummy. The slope of the term structure is the constant maturity 10-year Treasury bond yield less the 3-month Treasury bill yield. The corporate bond spread is Moody's BAA-rated bond yield less the AAA-rated bond yield. The descriptive statistics of these variables can be found in Table 8.2, Panel A. We use a 60-month rolling window regression of the market return on the lagged variables and use these parameter estimates to predict next month's market return. The difference between the observed market return and its prediction is called the market surprise. In our terminology, fund managers who are to some extent able to predict this surprise are expert market timers. In Table 8.2, Panel B we display the summary statistics of our market return prediction model. As can be seen from this table, the correlation of 0.14 between the predicted market return and the actual market return is modest over the full sample period. In the most recent part of the sample, the correlation becomes even negative, with –0.16 over the last three years. It seems that the out-of-sample ability of this linear model to forecast movements in the stock market is low.[9]

[7]We also plot the estimation results for selectivity and timing for each fund in Table 8.1. Summarized results are discussed in the remainder of this section.

[8]Ferson & Schadt (1996) use the dividend yield on the CRSP value weighted market return. We use the dividend yield on the S&P 500 instead, but expect this to have minor influence on the results.

[9]Unreported results indicate that our main conclusions do not materially change when no predictability

Table 8.1: **Descriptive statistics of asset allocation funds.** In this table the names of the funds from our sample are listed, together with some descriptive statistics. The column indicated with "Ave" contains the average monthly returns (in percentages) over the period 1995–2002. The column with "Std" contains the standard deviation over this period. The columns "Exp" and "Turn" contain the average expense ratio and turnover, over the fund's entire history. The columns "Alpha" and "Timing" contain the estimation results for the selectivity and timing return of these asset allocation funds.

Nr	Fund name	Average	StDev	Expense	Turnover	Alpha	Timing
1	Advantus Spectrum A	0.69	4.04	1.24	113.27	-0.111	0.000
2	Amer Funds Income Fund A	1.02	2.23	0.65	35.15	0.149	0.011
3	Aon Asset Allocation	0.95	3.29	0.68	70.17	-0.104	0.029
4	AXP Managed Allocation A	0.61	3.16	0.89	94.31	-0.105	0.000
5	Barclays Gbl Inv AA	0.93	3.11	0.76	40.71	-0.026	-0.004
6	Barclays Gbl Inv LP 2010	0.80	2.04	0.95	55.17	-0.113	0.073
7	Barclays Gbl Inv LP 2020	0.88	2.99	0.95	46.00	-0.107	0.046
8	Barclays Gbl Inv LP 2030	0.97	3.63	0.95	34.33	-0.076	0.026
9	Barclays Gbl Inv LP 2040	1.02	4.31	0.95	31.80	-0.058	-0.004
10	Barclays Gbl Inv LP Inc	0.63	1.11	0.95	70.40	-0.139	0.099
11	Berwyn Income	0.78	1.72	1.37	29.77	0.302	-0.082
12	Bruce	1.29	4.44	2.18	24.06	0.192	-0.207
13	Caldwell Orkin Mkt Opp	1.17	2.66	1.41	289.70	0.423	-0.087
14	Capital Val Inv	0.82	5.02	2.48	31.20	-0.162	0.417
15	Country Asset Allocation	0.87	2.56	1.41	30.88	-0.062	0.130
16	Deutsche Emerg Gr A	1.11	10.37	1.46	60.23	-0.289	-0.016
17	Deutsche Life Mid Invm	0.79	1.91	1.00	202.86	-0.121	0.110
18	Deutsche Life Shrt Invm	0.67	1.18	1.00	263.43	-0.152	0.136
19	Eclipse Asset Manager	1.01	2.84	0.71	84.20	0.071	0.029
20	Elfun Diversified	1.00	2.53	0.49	78.50	0.112	-0.001
21	Enterprise Managed A	0.81	4.02	1.57	50.50	-0.158	-0.100
22	EquiTrust Managed	0.71	2.37	1.95	65.50	0.333	-0.222
23	EquiTrust Value Growth	0.44	4.03	1.26	71.61	-0.278	0.000
24	Exeter Blended Asset I A	0.79	2.06	1.20	58.00	-0.057	0.076
25	Exeter Blended Asset IIA	1.03	3.04	1.17	74.40	-0.007	0.080
26	Federated Kaufmann K	1.35	6.43	2.27	116.25	0.657	-0.299
27	Federated Mgd Con Gr Ins	0.58	1.70	1.03	93.50	-0.158	0.043
28	Federated Mgd Gr Ins	0.64	3.51	1.09	100.71	-0.270	0.007
29	Federated Mgd Mod Gr Ins	0.65	2.64	1.04	95.57	-0.199	0.024
30	Fidelity Asset Mgr: Inc	0.63	1.23	0.70	125.33	0.014	0.035
31	Fidelity Value	1.18	4.72	1.00	171.43	0.278	-0.120
32	Fifth Third Str Inc Adv	0.71	1.41	1.94	103.60	0.083	-0.020
33	First Inv Total Return A	0.79	2.91	1.26	115.22	-0.354	0.169
34	Flex-funds Muirfield	0.71	3.84	1.33	286.67	-0.226	0.073
35	FMI AAM Palm Beach T/R	0.99	4.52	1.95	49.77	0.126	-0.029
36	Gabelli ABC	0.74	1.19	1.96	397.25	0.262	-0.023
37	Gabelli Mathers	0.12	1.53	0.89	207.50	0.079	-0.139
38	Galaxy Asset Alloc Ret A	0.80	2.70	1.30	59.88	-0.120	0.044
39	GE Strategic InvestmentA	0.95	2.55	0.85	102.13	0.067	-0.035
40	General Securities	0.71	5.36	1.46	44.27	-0.345	0.347

Table 8.1: **(continued):**

Nr	Fund name	Average	StDev	Expense	Turnover	Alpha	Timing
41	Guardian Asset Alloc A	0.91	3.39	0.95	95.00	-0.084	0.004
42	Hartford Advisers HLS IA	0.98	2.96	0.66	40.00	-0.018	0.035
43	ING Ascent I	0.77	3.50	1.30	165.83	0.034	-0.057
44	ING Crossroads I	0.69	2.74	1.29	160.00	0.059	-0.067
45	ING Legacy I	0.67	1.89	1.29	141.00	0.044	-0.024
46	INVESCO Growth Inv	0.63	9.16	0.85	125.64	-0.022	0.010
47	MegaTrends	0.81	4.56	1.83	104.50	-0.131	0.137
48	Montgomery Balanced R	0.70	2.92	0.78	97.14	-0.073	0.121
49	Morgan Stanley Strateg B	0.88	3.29	1.54	129.58	-0.008	-0.017
50	Nations Asset Alloc InvA	0.88	2.84	0.78	104.38	-0.053	0.061
51	One Group Balanced A	0.85	2.61	1.17	69.13	-0.108	0.067
52	Oppenheimer Discip Alc A	0.61	2.50	1.14	123.76	0.016	-0.088
53	Oppenheimer Quest Opp A	1.09	3.53	1.77	55.42	0.143	0.000
54	Phoenix-Oakhurst Str A	0.84	3.15	1.33	236.63	-0.091	0.061
55	Preferred Asset Alloc	0.97	2.78	1.03	25.33	0.047	-0.030
56	Sand Hill Portfolio Mgr	0.57	3.46	1.88	33.67	-0.258	0.060
57	Scudder Dynamic Growth A	0.61	9.66	0.89	89.12	-0.021	-0.023
58	Seligman Income A	0.41	2.18	0.87	68.96	-0.029	-0.034
59	Smith Barney Soc Aware B	0.83	3.29	2.04	65.62	-0.070	0.016
60	State St Res Str Gr A	0.96	3.12	1.27	113.83	0.068	-0.033
61	Strong Balanced	0.66	3.15	1.24	252.72	0.037	0.120
62	T. Rowe Price Pers Bal	0.92	2.43	1.03	44.86	0.114	-0.059
63	T. Rowe Price Pers Inc	0.82	1.79	0.93	47.86	0.084	-0.023
64	UBS Tactical Allocation C	1.11	4.23	1.80	40.00	-0.137	0.026
65	Valley Forge	0.61	2.31	1.69	43.29	0.046	0.012
66	Value Line Asset Alloc	1.28	4.31	1.14	152.25	0.554	-0.274
67	Vanguard Asset Alloc	1.09	3.04	0.48	35.33	0.135	-0.015
68	Vanguard LifeSt Cons Gr	0.83	1.91	0.00	5.00	0.035	0.035
69	Vanguard LifeSt Growth	0.94	3.55	0.00	3.00	-0.034	-0.009
70	Vanguard LifeSt Income	0.78	1.27	0.00	9.57	0.079	0.050
71	Vanguard LifeSt Mod Grth	0.90	2.73	0.00	6.00	-0.002	0.019
72	Wells Fargo Asset All A	0.93	3.11	0.94	52.85	-0.098	0.134
73	Wells Fargo Index All A	0.98	4.33	1.39	40.92	0.077	-0.002
74	Wells Fargo Outlook TdyA	0.59	1.11	1.24	59.00	-0.179	0.103
75	Wells Fargo Outlook2010A	0.77	2.04	1.24	47.00	-0.101	0.050
76	Wells Fargo Outlook2020A	0.86	2.98	1.24	43.00	-0.107	0.038
77	Wells Fargo Outlook2030A	0.94	3.64	1.24	29.75	-0.100	0.023
78	Wells Fargo Outlook2040A	0.98	4.32	1.24	28.00	-0.099	0.000
	Average	0.83	3.24	1.17	90.51	-0.012	0.013

Table 8.2: **Descriptive statistics of the predicted market return.** In Panel A we present descriptive statistics of our prediction variables for several subsamples. We use a 60 month rolling OLS regression to estimate the predictive model parameters. In addition to the constant, five predictive variables are used: the level of short interest rate, the dividend yield, the term spread, the default spread, and the January dummy. For the prediction of the market return of June 1972, we estimate the regression parameters on the sample June 1967 – May 1972, and use these to predict the market return of June 1972. This is repeated by moving the estimation sample forward each month. The column labeled "Predict" in Panel B contains the average monthly predicted return, "Realized" contains the realized excess market return over the same period, "Correlation" denotes the correlation coefficient between the predicted and realized market returns, and "SigSurprise" contains the volatility of the surprise market return over the sample, which is defined as the realized market return less the predicted market return.

Panel A

Sample		T-Bill	Div. yield	Default	Term	January
1972:6-2002:5	average	6.58	3.45	1.10	0.90	0.08
	stdev	2.72	1.35	0.45	1.16	0.28
1972:6-1982:5	average	8.15	4.57	1.26	0.12	0.08
	stdev	3.26	0.96	0.50	1.22	0.28
1982:6-1992:5	average	7.19	3.83	1.28	1.39	0.08
	stdev	1.65	0.72	0.39	0.78	0.28
1992:6-2002:5	average	4.40	1.96	0.74	1.17	0.08
	stdev	1.15	0.67	0.17	1.00	0.28

Panel B

Sample		Predict	Realized	Correlation	SigSurprise
1972:6	2002:5	0.693	0.463	0.136	4.89
1972:6	1982:5	0.572	-0.094	0.171	5.22
1982:6	1992:5	0.702	0.851	0.233	4.73
1992:6	2002:5	0.805	0.631	-0.068	4.70
1992:6	1999:12	0.895	1.217	-0.071	4.22
2000:1	2002:5	0.521	-1.207	-0.164	5.76

8.4 Performance attribution of asset allocators

In order to obtain the estimated return components as derived in Section 8.2 of this chapter, we estimate the following model for the conditional fund returns from equation (8.8)

$$\begin{aligned} R^e_{i,t} &= \alpha_i + \beta_{i,t} R^e_{m,t} + \varepsilon_{i,t} && (8.9) \\ \beta_{i,t} &= \overline{\beta}_i + \rho_i \left(\beta_{i,t-1} - \overline{\beta}_i\right) + \delta_i' X_{t-1} + \tau_i \left(R^e_{m,t} - \widehat{R}^e_{m,t}\right) + \eta_{i,t}, && (8.10) \end{aligned}$$

where $\widehat{R}^e_{m,t}$ is the predicted market return based on publicly available information. We assume that the error terms $\varepsilon_{i,t}$ and $\eta_{i,t}$ are independently and normally distributed with variances σ^2_ε and σ^2_η. The parameters of interest of the model, α_i, ρ_i, δ_i, τ_i, and the series of parameters $\beta_{i,t}$ follow from maximum likelihood estimation and the Kalman filter, respectively.[10] We define the mean-reversion term as $\beta^*_{i,t} = \rho_i \left(\beta_{i,t-1} - \overline{\beta}_i\right)$.

In state-space terminology, equation (8.9) is called the measurement equation, and equation (8.10) is called the transition equation. Under the normality assumption, the Kalman filter is the minimum mean square estimator for the parameters $\beta_{i,t}$. When the disturbances are not normally distributed, the Kalman filter is still the minimum mean square linear estimator. Thus, the Kalman filter is optimal in this sense if we restrict our attention to estimators that are linear in the observations. The $\beta_{i,t}$-s follow from recursions based on the fit of the observed data $\left(R^e_{i,t}, R^e_{m,t}, X_{t-1}\right)$ with the specified measurement and transition equation, in combination with the assumptions about the error terms. For more details on the Kalman filter and its properties see, e.g., Harvey (1993).

We constrain the parameter ρ_i to be between zero and one. Economically, the exclusion of negative values of ρ_i means that we do not allow the exposure to oscillate monthly around its long-run average. In other words, an exposure below (above) the long-run average in this month is not allowed to imply an exposure above (below) the long-run average next month. The restriction that ρ_i is below one prevents an explosive market exposure, which would become unrestrictedly large as time goes by. The macro economic variables as well as the market surprise are demeaned, in order for the interpretation of $\overline{\beta}_i$ to be the funds average exposure. The inferences about timing or selectivity are not affected by this transformation.

The model from (8.9)–(8.10) is estimated for each of the 78 funds from our sample of asset allocation funds. Summary statistics of the estimated coefficients can be found in

in the market return is assumed. In that case, expert timing reduces to the usual notion of timing.

[10]Without the mean-reversion term in the market exposures, the model reduces to a linear regression model with heteroskedastic errors. We estimate the model with Ssfpack, described in **?**.

Figure 8.1: Decomposition of conditional mutual fund returns. For the 7 factors in our decomposition, we display the median value (horizontal line) and the 40 percent of funds below and above the median (vertical line). The numbers on the y-axis are basis points per month. Bstar denotes the the mean-reversion component and Bbar the long-term target exposure.

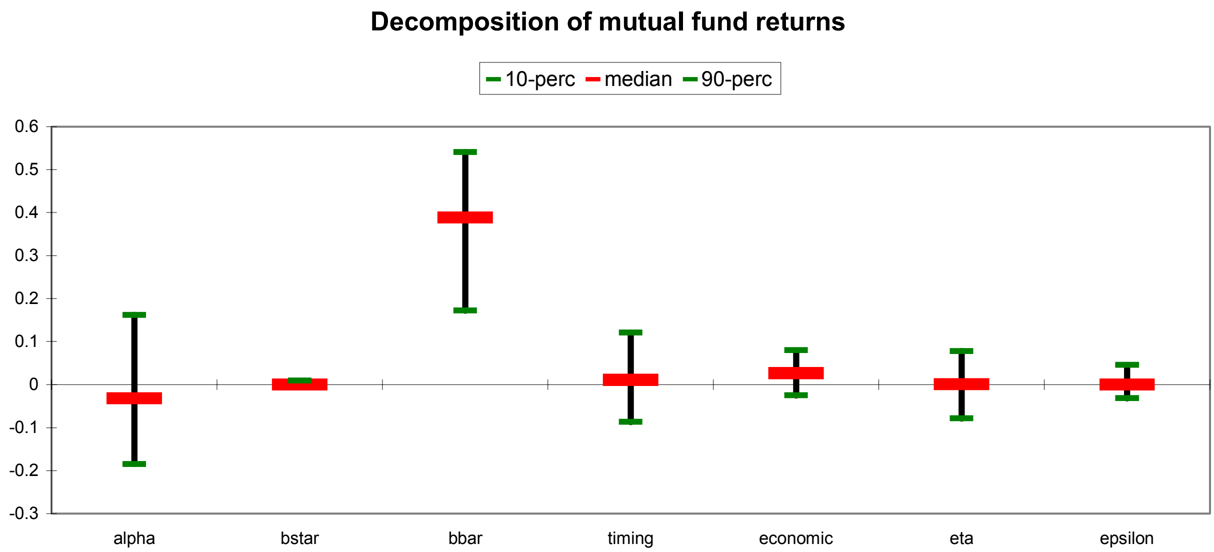


Table 8.3: **Parameter estimates for model with dynamic exposures.** The parameter estimates from equation (8.9)– (8.10) are displayed. For each parameter, the cross-sectional average, the 10-percentile, the median, and the 90-percentile are tabulated. The standard deviations from the hyperparameters η and ε are also included, as well as the time-series minimum and maximum estimate for the market exposure β.

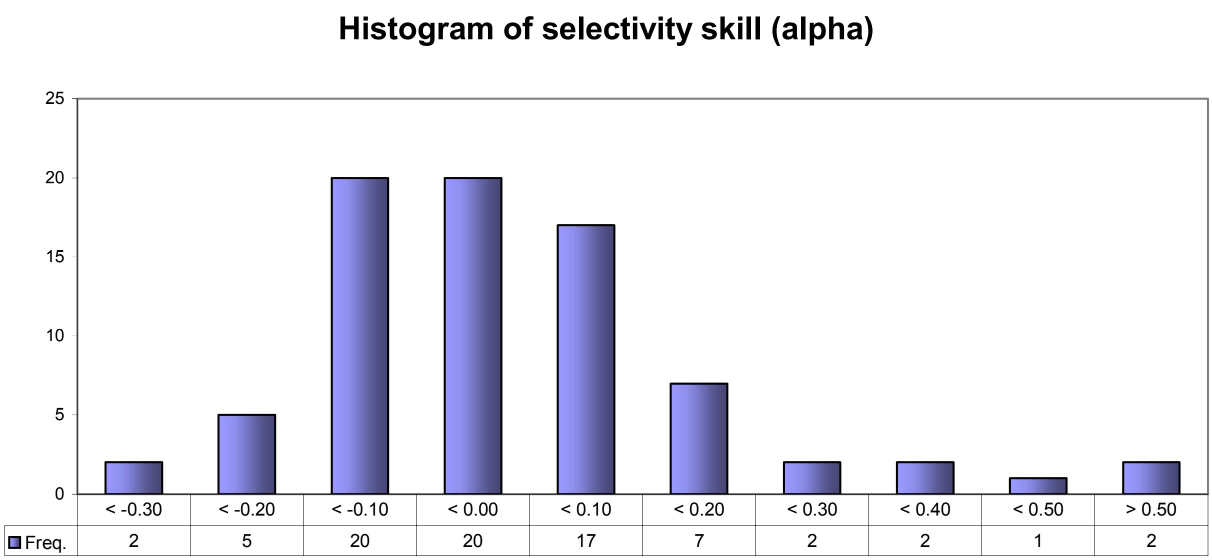
Parameter	Min.	Mean	Max.	10-perc	median	90-perc	sign +	sign -
alpha	-0.35	-0.01	0.66	-0.18	-0.03	0.16	4	4
long-run beta	0.12	0.60	1.53	0.26	0.61	0.88	78	0
timing * 100	-1.51	0.06	2.36	-0.44	0.05	0.54	6	1
dividend yield	-0.42	0.05	0.46	-0.08	0.06	0.16	25	6
term spread	-0.43	-0.02	0.33	-0.09	-0.02	0.07	3	5
default spread	-1.07	-0.16	0.45	-0.42	-0.17	0.14	1	13
interest rate	-3.31	-0.35	1.09	-0.90	-0.35	0.26	0	11
january dummy	-0.22	0.04	1.18	-0.09	0.01	0.19	3	12
rho	0.00	0.12	0.93	0.00	0.01	0.40	–	–
stdev eta	0.00	0.15	0.83	0.01	0.12	0.32	–	–
stdev epsilon	0.48	1.24	5.49	0.61	0.92	2.11	–	–

Table 8.3. The estimated parameters are used to compute the conditional return decomposition from equation (8.4). In the remainder of this section, we analyze the importance of each of the factors of this decomposition. This provides insights in the economic magnitudes of time-variation in market exposures, timing ability, and selection ability of mutual funds with an asset allocation aim. A graphical overview of the importance of the factors we discriminate in our analysis is provided by Figure 8.1. The median value and the estimated return for the fund at the 10 and 90 percent interval are displayed. A long vertical bar for a component indicates that return dispersion attributed to that factor is high.

8.4.1 Manager skills: Selectivity and timing

First, consider the selectivity or micro-forecasting component, which is reflected by α_i in equation (8.9). Since the primary objective of the funds is asset allocation, we do not expect to find economically significant positive α-s. Figure 8.2 shows the distribution of the selectivity parameter of the funds in our sample. This figure indicates that the selectivity skill is spread around zero, with 47 out of 78 funds having a negative estimate for alpha. The distribution of alphas is somewhat skewed, with five funds exceeding 30 bp per month and only two funds falling below –30 bp. The estimation summary in Table 8.3 shows a negative alpha of –3 bp for the median asset allocation fund. The dispersion in manager selectivity indicates the risk for the investor from picking the right or wrong manager, all other things equal. The 80 percent interval of alphas around the median ranges from -18 bp to 16 bp per month. Thus, while the median alpha is close to zero, selection of one

Figure 8.2: Histogram of estimated selectivity skill.



particular asset allocation fund might lead to a substantial variation in manager selectivity. There are only a few funds for which the α_i-s are statistically significant. We find four funds with a statistically significant positive, and four funds with a significantly negative selectivity coefficient. This is just over 10 percent of our sample, yet larger than the 5 percent we would expect if all managers in the sample have no selectivity.

The traditional timing skill of the fund manager is measured by the correlation of the fund's exposure to the market with the excess return on the market in the same month. Ferson & Schadt (1996) argue that the market is to a certain extent predictable, and timing related this public market forecast should not be attributed to manager ability. A private investor could, in principle, replicate such strategy himself at relatively low cost, because it is based on publicly available information. However, the return differential between the market and the predicted component cannot be forecasted by the private investor, and this expert timing provides insight in the true skills of the manager. In Figure 8.3 we summarize the estimation results for the expert timing coefficient, represented by τ_i in equation (8.10). For 47 funds we find a positive estimate, which is somewhat higher than the 39 we would expect if managers have no timing skill. In Table 8.3 we see that the median timing coefficient is slightly positive with 0.0005. From equation (8.6) we know that the expected gains from expert market timing depend on the conditional variance in the surprise market return. The average return due the timing component is 1.2 bp per month.[11] The 80 percent interval for the timing return is -8.7 to 12.1 bp per month. In order to obtain an overview, Figure 8.1 displays the dispersion from each of the factors influencing the average return. The timing interval is only half the size of the interval of the selectivity return computed above. Note that the statistical significance of the timing parameter is limited. We find six statistically significant positive estimates, while just one is significantly negative. If there would be no timing, we would expect two positive and two negative rejections. Hence, albeit not overwhelming, our results indicate that there is evidence supporting timing ability for some mutual fund managers. However, note that our sample consists only of surviving funds, which might bias our timing results in favor of timing.

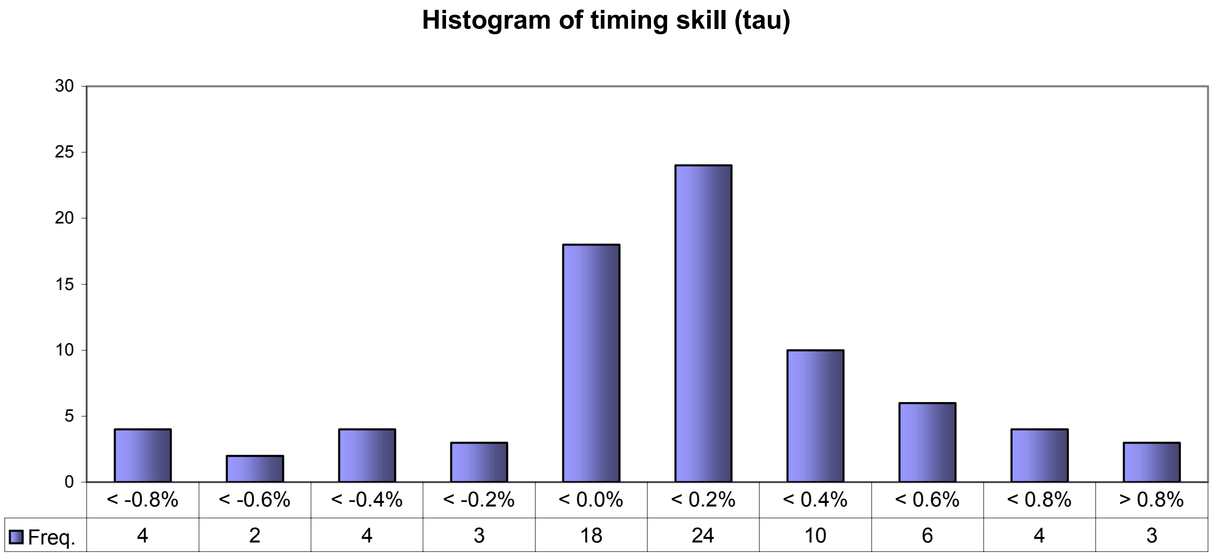
The estimates for selectivity and timing at the individual fund level can be found in Table 8.1. The results on selectivity and timing suggest that an investor who is able to select the fund with both top decile alpha and timing might have an expected return of 55.5 bp per month over an investor selecting the bottom decile alpha and timing.[12] This is true if the decision about selectivity and timing can be separated from each other. However, the benefits of management skills for private investors are reduced if managers with positive (negative) timing ability at the same time have negative (positive) selectivity. Most empirical studies find that the correlation between selectivity and timing is negative, suggesting that high (low) timing corresponds to low (high) selectivity. Glosten & Jagannathan (1994), among others, indicate that there is an economic explanation for this result. Managers might purchase put options, which lead to reduced market exposures when stock returns are low, implying timing ability. Obviously, this type of timing is artificial and is unrelated to manager skill. The cost of buying put options is reflected in lower manager selectivity. We also examine the combination of returns due to selectivity and expert timing to gauge the potential expected return difference that investors in a fund can obtain due to good management.

The correlation between the returns due to selectivity and expert timing in our sample is –0.71, which is consistent with the hypothesis that the manager is buying options rather than being a true market timer. Another explanation is provided by Edelen (1999), who claims that providing liquidity to accommodate inflow and outflow of money affects timing measures. However, the results from Edelen suggest that using conditional performance measures such as Ferson & Schadt (1996) accounts for these liquidity effects. We find that for each of the eight funds with significant α-s, the corresponding τ-s are of the opposite sign, of which three are also statistically significant. The average return of the sum of

[11]Since not all funds from our sample exist over the entire 1972-2002 period, the reported gains from timing do not equal $0.0006 \cdot (4.88)^2 = 1.4$ bp. The somewhat lower volatility in the '90-s might cause the marginally lower reported average fund timing returns of our sample.

[12]This follows from $55.5 = (16.2 + 12.1) + (18.5 + 8.7)$.

Figure 8.3: Histogram of estimated expert timing skill.



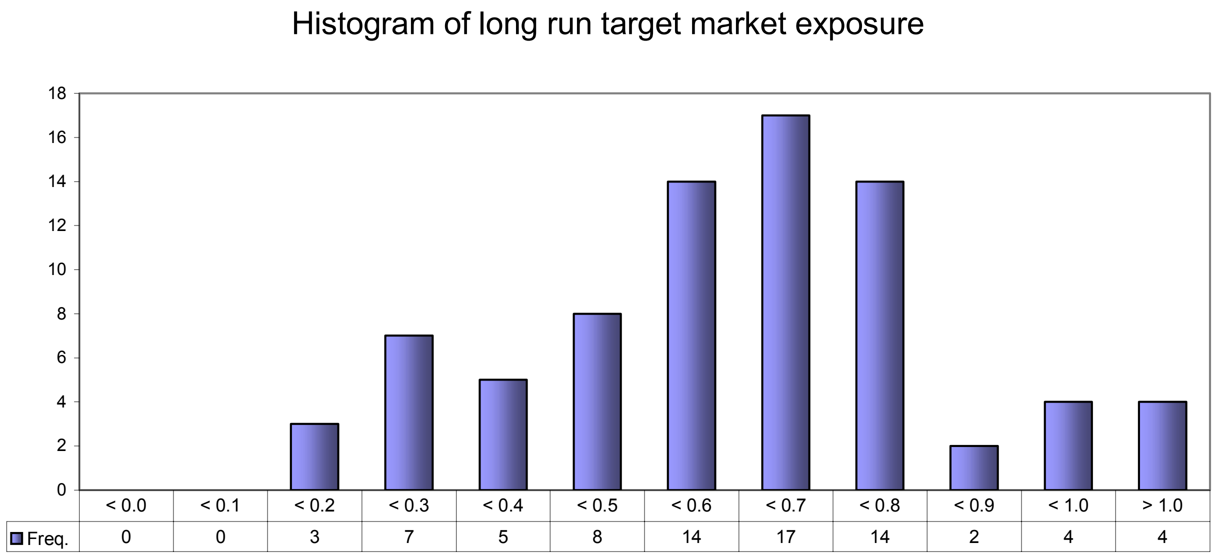
selectivity and timing is close to zero, and the 80 percent spread of the sum is from –0.13 to 0.16 bp. The size of this spread in total manager skill (29 bp) is considerably lower than the sum of the spread in alpha (35 bp) and the timing return (21 bp). This indicates that private investors cannot exploit both selectivity and expert timing skill at the same time. An investor who picked a fund with adverse selectivity skill enjoys this negative relation, since most likely the expert timing skill of the fund manager partially compensates the losses on selectivity. Nevertheless, manager skill dispersion amounts to a return difference of 3.5 percent per annum, which indicates the importance of selecting the mutual fund with the best manager.

8.4.2 Non-skill components of conditional expected return

We now turn to analyzing the components of expected return not related to manager skill. The three remaining components are the long-term market exposure, mean-reversion or delayed reaction, and macro economic sensitivities. These three components can also be found in the decomposition of conditional fund returns in equation (8.8).

A histogram of the estimates of the long-term market exposures is displayed in Figure 8.4. The median fund has a long-term exposure to the market of 0.61. The dispersion in these unconditional market exposures ranges from 0.26 to 0.88, excluding the top and bottom decile. The long-term market exposure is below one for all but 4 funds, indicating that most funds are on average only partially exposed to stock market risks. This can be

Figure 8.4: Histogram of estimated long-run market exposure.



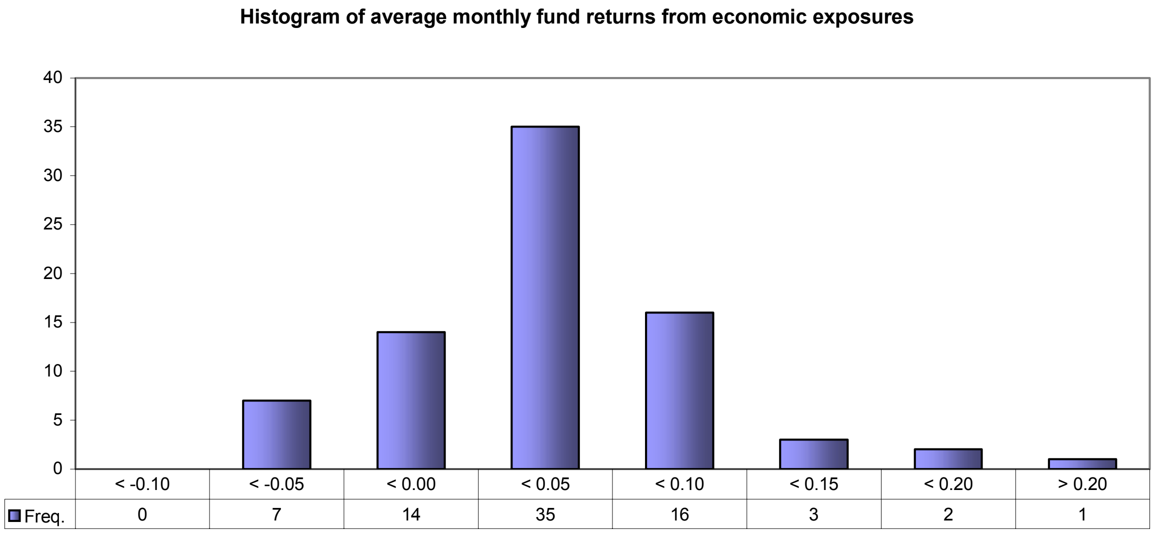
achieved by investing in, for example, bonds or cash, but also by investing in low beta stocks. In the latter case, information about the holdings in asset classes, as provided by for example Morningstar, would not suffice to find a low market exposure. Edelen (1999) indicates that mutual funds are less exposed to the stock market because they need cash in their portfolio in order to accommodate the inflow and outflow of investor's money. The expected return that can be attributed to this component is the long-term exposure multiplied by the conditionally expected risk premium. The average fund return related to the long-term exposure is 34 bp per month.[13]

The component that captures delayed reaction to past signals to deviate from the long-run target exposure seems to be of minor importance for this particular empirical application. In total 51 funds have a mean-reversion coefficient below 0.05, indicating that most funds adapt their exposures quickly.[14] On the other hand, for eight funds this term is above 0.40, suggesting economic importance in certain cases. Leaving out this component might lead to biased estimates for the other parameters in the model. This mean-reversion

[13] Since the funds in our sample have different starting dates, the average return due to this component is a product of the long-term market exposure and a weighted average of the excess market returns. The lower average market return in the first 10 years is underweighted because only a couple of funds existed back then.

[14] See Alexander et al. (1982) for a discussion on the random walk specification of the market exposure of mutual funds engaged in market timing or variability in the beta of stocks in the mutual fund portfolio. The mean-reversion specification used here reduces to the random walk specification when the mean-reversion parameter ρ is equal to one.

Figure 8.5: Histogram of estimated average return due to macro exposures.



component measures temporary deviations from the long-run average, and hence its total effect is expected to be around zero. The small impact of returns attributable to this factor is also found in the data. The fund with mean-reversion at the 90th percentile can attribute on average only 1 bp to this factor.

The sensitivities to economic variables are used both directly and indirectly in our estimation of the market exposure. In addition to the term $\delta_i' X_{t-1}$ in equation (8.9), the predicted market return is also a linear combination of the same macro variables. Thus $-\tau_i \widehat{R}_{m,t}$ can be rewritten as $\widehat{\phi}_i' X_{t-1}$, where $\widehat{\phi}_i$ is a linear function of the expert timing coefficient (τ_i) and the parameters from our predictive market return model ($\widehat{\gamma}$). The δ_i represents the macro sensitivities that are not explained by the expert timing behavior of the mutual fund manager. The returns from the explicit part can be interpreted as macro sensitivities of the fund deviating from the optimal macro exposure for timing. Figure 8.5 shows that mutual fund returns from direct macro economic exposures are modest. About 75 percent of the funds achieve a positive average return from this component. This result suggests that managers are able to increase fund returns by using economic information deviating from the public forecast as specified in our model. The average contribution of this factor is small, with 2.8 bp per month. The interval after deleting the 10 percent highest and lowest returns reaches from -2.5 to 8.0 bp, and is about half the size of the timing component. Investigating the statistical significance of the sensitivities to the individual macro variables shows that more than 5 percent is rejected at the 95 percent level for each of the five variables separately. The estimated coefficient for the dividend yield is statistically significant at the 95 percent level for 40 percent of the funds. The lowest number of rejections are for the term spread, but with 10 percent this is still more than the 5 percent significance level of the test. See Table 8.3 for more details. These results indicate that mutual fund managers are able to use economic information to increase returns above the public forecast.

8.4.3 Time-series variability in the market exposures

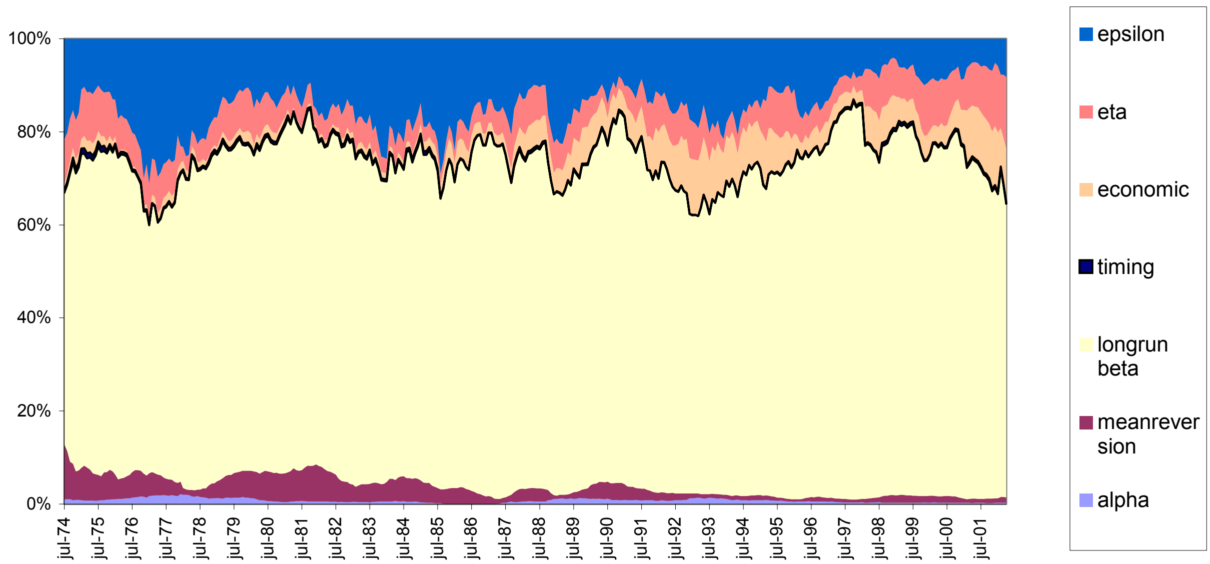
The importance of allowing market exposures to change over time for performance evaluation depends on the variation employed by these managers. In order to motivate the use of a dynamic process for the market exposure, as in equation (8.10), we examine the minimum and maximum estimated exposure for each of the funds in our sample. The summary statistics of this analysis are displayed in Table 8.3. The median from the time-series minima for our 78 mutual funds is 0.21, while the median from the time-series maxima is 0.92. This indicates that the estimated market exposures vary considerably over time for these funds. These findings suggest further that many funds tend to hold cash, probably for liquidity reasons as suggested by Edelen (1999). Also, many funds do not fully hedge their market exposure when they expect stock markets to have negative returns. The findings on this difference between the minimum and maximum exposure motivate the use of our dynamic approach to mutual fund performance evaluation.[15]

Equation (8.10) contains a random exposure shock, $\eta_{i,t}$, to allow for market exposure changes unrelated to the other components of the model. These random changes represent uncertainty in the market exposure that does not influence the conditional expected return. For example, this term includes exposure shocks due to management change. For several funds our estimation results indicate that the term $\eta_{i,t}$ is unimportant. This can be seen in Table 8.3, where the lower 10th percentile of $\widehat{\sigma}_\eta$ is 0.01. For the median fund $\widehat{\sigma}_\eta = 0.12$, which suggests that random market exposure changes can be sizeable, corresponding to a 95%-confidence interval of 0.48. These random changes in beta also influence the total variance of the conditional expected return. Conditional on the market return, the variance is increased by $\sigma_\eta^2 \left(R_{m,t}^e\right)^2$. This gives an impression of the variability of the unexplained fund returns that can be attributed to random variation in the market exposure.

The residual variance of the fund return is $\sigma_\eta^2 \left(R_{m,t}^e\right)^2 + \sigma_\varepsilon^2$. For the median fund, the second term is estimated to be $\widehat{\sigma}_\varepsilon = 0.92$ percent per month. In contrast to equity mutual funds, for which most of the return variation can be explained by standard factor models, these fund returns behave differently. Apparently, most funds are not fully diversified, and potential investors should be aware of this when deciding about adding an asset allocation

[15]Recently, Spiegel et al. (2003) also use a dynamic state-space model in order to select mutual fund managers.

Figure 8.6: Relative importance of components in the mutual fund return decomposition. The return is split up in 7 parts $R^e_{i,t} = \alpha_i + \rho_i \left(\beta_{i,t-1} - \overline{\beta}_i\right) R^e_{m,t} + \overline{\beta}_i R^e_{m,t} + \tau_i \left(R^e_{m,t} - \widehat{R}^e_{m,t}\right) R^e_{m,t} + \delta_i' X_{t-1} R^e_{m,t} + \eta_{i,t} R^e_{m,t} + \varepsilon_{i,t}$, which are displayed in the figure in the same order from the bottom to the top of the figure. The relative importance is calculated by $share_{i,t} = \frac{|c_{i,t}|}{\sum_{i=1}^{7} |c_{i,t}|}$, where $c_{i,t}$ is the cross-sectional average of component i at time t.



fund to their portfolio. A graphical representation that indicates the importance of these residuals can be found in Figure 8.6, in which the time-series properties of the sample of funds are analyzed in more detail. To construct this figure, each of the 7 components of $R^e_{i,t}$ from equation (8.9) are equally weighted over the 78 funds in our sample. Thus, we obtain cross-sectional averages of the components on the right-hand side of

$$R^e_{i,t} = \alpha_i + \overline{\beta}_i R^e_{m,t} + \rho_i \left(\beta_{i,t-1} - \overline{\beta}_i\right) R^e_{m,t} + \delta_i' X_{t-1} R^e_{m,t} + \tau_i \left(R^e_{m,t} - \widehat{R}^e_{m,t}\right) R^e_{m,t} + \eta_{i,t} R^e_{m,t} + \varepsilon_{i,t} \tag{8.11}$$

for each point of our sample. This cross-sectional average can be interpreted as a fund-of-fund with equals weights in each of the individual asset allocation funds. If we denote these cross-sectional averages by $\overline{c}_{j,t}$, it is possible to calculate the average contribution of each of the components over time as

$$share_{j,t} = \frac{|\overline{c}_{j,t}|}{\sum_{i=1}^{7} |\overline{c}_{j,t}|}.$$

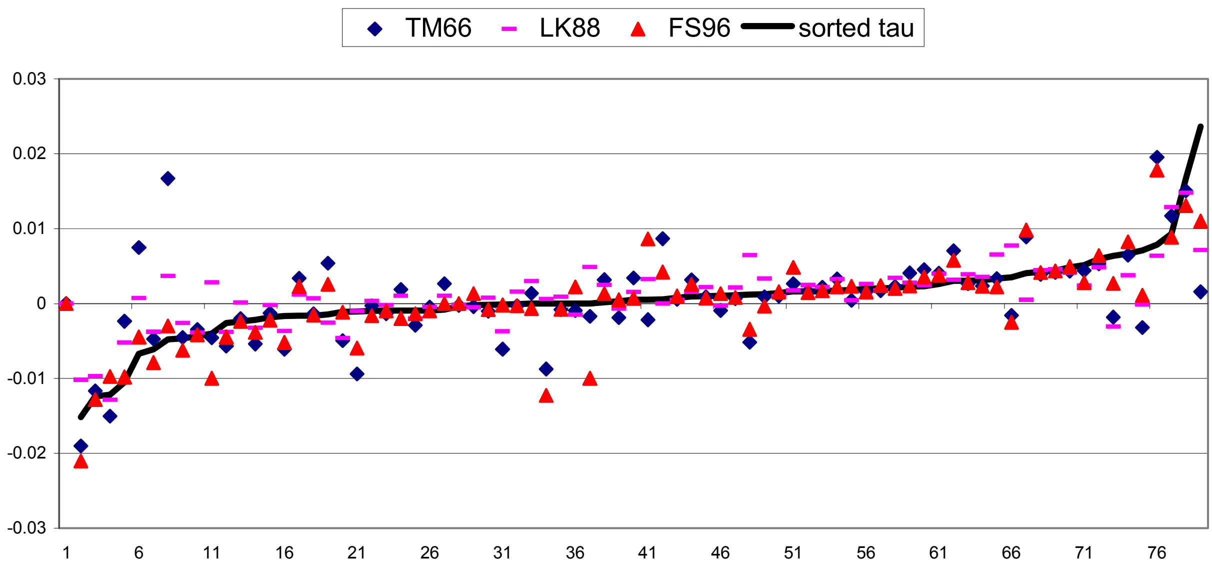
The annually smoothed shares $share_{i,t}$ are plotted in Figure 8.6. As can be seen, the most important part can be explained by the long-term beta exposure. Both selectivity and timing do not appear to be important. Note that the error terms ε and η are correlated over firms, as they can make a substantial contribution to fund returns. From 1992–2002, the contribution of ε decreased substantially. This indicates that idiosyncrasies in fund returns can be diversified better towards the end of the sample. At the same time, the influence of η is stronger at the end (and beginning) of the sample period. This allows for the possibility that there is a common component in the unexplained changes in the manager's market exposure changes against which an investor cannot diversify away by investing in many funds. We also observe an increased importance of the macro economic factors in the first half of the 1990s. This suggests that mutual fund managers were reacting similarly on on macro economic information during this 5-year period.

8.4.4 Relation with other models

For the return decomposition above, we used the dynamic model as described in equations (8.9)–(8.10). As noted earlier, under certain parameter restrictions these models reduce to well-known performance evaluation models. In this subsection, we analyze the differences in estimated manager skills by using our extended model and the restricted models from the existing literature.

In order to investigate this, we have graphically displayed the coefficients from our model in ascending order. This is represented by the black line in Figure 8.7. The corresponding estimates from the stochastic timing model Lockwood & Kadiyala (1988) are

Figure 8.7: **Estimated market timing skills across different models.** For each of the 78 asset allocation funds in our sample, we estimate the model with time-variation in market exposures using our model and three well-known performance evaluation models; Lockwood and Kadiyala (1988, LK88), Ferson and Schadt (1996, FS96) and Treynor and Mazuy (1966, TM66). We rank the funds on the basis of the timing estimate from our model, and display the timing estimates that result from the other models. The closer the symbols to the black line, the closer the timing estimate from that model corresponds to the timing measure from our model.



displayed in rectangles, the conditional timing model Ferson & Schadt (1996) in triangles, and the traditional timing model Treynor & Mazuy (1966) in diamonds. As could be expected, the existing performance analyses are in many cases not much different from our model, since our model is a generalization and might reduce to the existing models depending on the mutual fund performance data. However, in notable cases the timing coefficients differ substantially, which can be seen by the dispersion of the dots at a certain point at the x-axis. Several funds that show excellent positive timing coefficients by the Treynor & Mazuy (1966) analysis, end up in the left part of the graph, suggesting weak timing skills when a more general model is analyzed. The reverse is also true, some funds with high timing skill according to our model, seem to have no timing according to the simple model. Moreover, some of the most negative timing funds by the Ferson & Schadt (1996) or positive timing funds from the Lockwood & Kadiyala (1988) model are in the middle of the graph, indicating no timing ability within our model. Misspecification of the performance evaluation model in such cases could lead to erroneous inference, and hence giving the wrong investment advice for potential investors in asset allocation mutual funds. The selectivity estimates seem more robust against the timing specification of the model, as can be seen from Figure 8.8. Although a couple of differences are substantial the models here show much more resemblance.

8.5 Turnover, expenses, and performance

The fund managers of our sample of asset allocation funds can be expected to actively change the market exposure of their fund. However, it is unclear whether funds with high or low turnover are successful market timers.[16] A related question is whether funds with higher expense ratios are expected to perform better. We analyze the relation between the selectivity and expert timing performance of the funds and their average turnover and expense ratio. How the average turnover and expense ratios evolve over time can be seen from Figure 8.9. As can be seen, turnover and expense ratios are somewhat higher in the middle of the sample period. Wermers (2000) also finds that funds have increased their turnover over time, but that expense ratios are fairly stable.

We rank the mutual funds by their average turnover (see Table 8.1 for the individual turnover and expense ratios), and divide them in eight groups. Each group consists of 10 mutual funds, except the middle two have nine. The averages of these groups can be found in Table 8.4, Panel A. The average turnover of the top and bottom groups is 19 and 247 percent. The average security in the group of funds with low turnover stays in the

[16]In addition, it is unclear on which horizon these funds time. We assume a monthly timing horizon, but in Goetzmann, Ingersoll & Ivkovic (2000) it is shown that daily timing ability may be hard to detect using monthly data.

Figure 8.8: **Estimated alphas across different models.** For each of the 78 asset allocation funds in our sample, we estimate the model with time-variation in market exposures using our model and three well-known performance evaluation models; Lockwood and Kadiyala (1988, LK88), Ferson and Schadt (1996, FS96) and Treynor and Mazuy (1966, TM66). We rank the funds on the basis of the alpha estimate from our model, and display the alpha estimates that result from the other models. The closer the symbols to the black line, the closer the selecivity estimate from that model corresponds to the selectivity measure from our model.

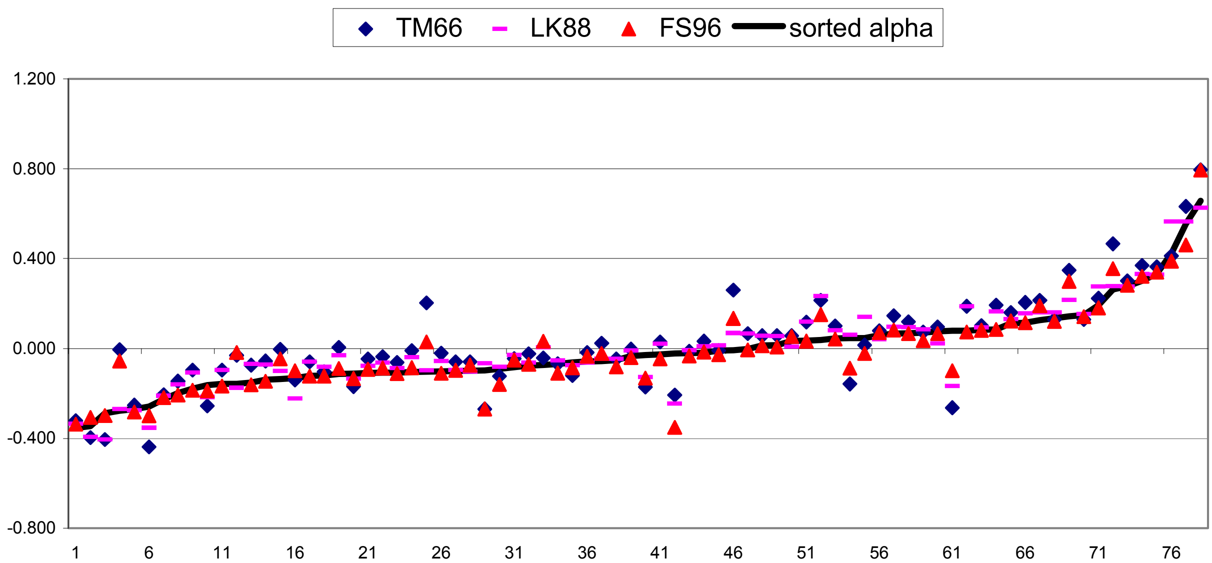


Table 8.4: **Relation between turnover, expenses, and management skill.** In the column with rank the bucket number is displayed, with each bucket consisting of 10 mutual funds, except bucket 4 and 5, which consist of only 9. In the subsequent columns the average raw returns (period 1995-2002), standard deviation, expense ratio, turnover rate, and the sum of selectivity (alpha) and timing returns (in percentages per year, calculated over entire sample period). In Panel A the funds are ranked on average turnover rate, and in Panel B on average expense ratio.

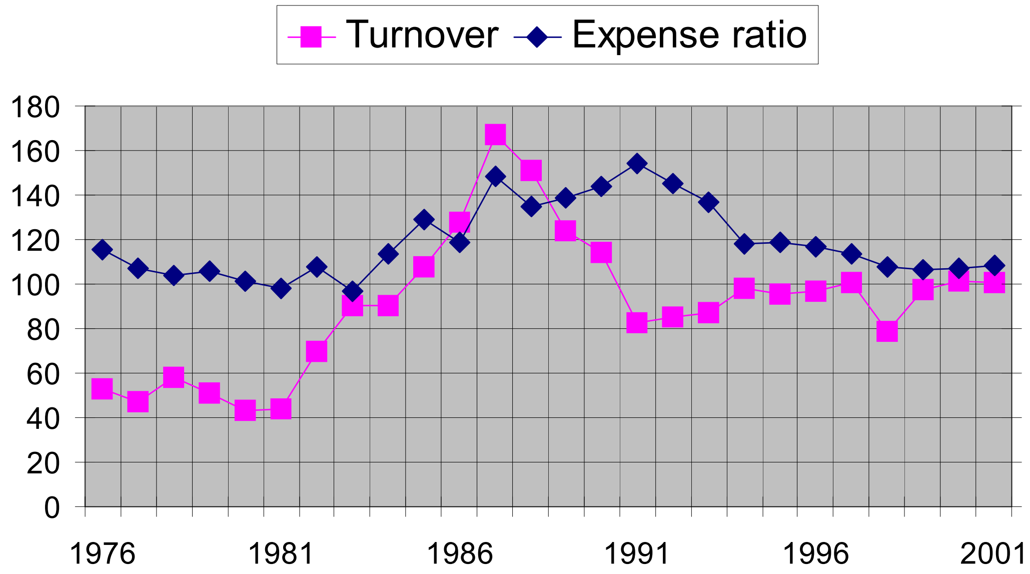
Panel A: Mutual funds ranked on average turnover rate.

	average return	expense ratio	turnover rate	alpha + timing	σ_η	σ_ε
sort 1	0.77	1.25	247.40	0.72	0.20	1.33
sort 2	0.85	1.28	130.29	0.53	0.17	1.38
sort 3	0.75	1.14	101.06	-0.69	0.12	1.02
sort 4	0.79	0.93	77.89	-0.41	0.15	1.27
sort 5	0.79	1.42	60.86	-0.45	0.12	1.58
sort 6	0.83	1.30	46.94	-0.15	0.13	1.34
sort 7	0.95	1.20	36.31	0.21	0.18	0.93
sort 8	0.93	0.85	19.14	0.35	0.09	1.12

Panel B: Mutual funds ranked on average expense ratio.

	average return	expense ratio	turnover rate	alpha + timing	σ_η	σ_ε
sort 1	0.88	2.05	99.14	1.04	0.25	1.81
sort 2	0.93	1.55	78.48	-0.02	0.22	2.03
sort 3	0.74	1.30	138.04	-0.57	0.19	1.15
sort 4	0.81	1.23	78.35	-0.31	0.11	0.94
sort 5	0.85	1.07	97.39	-0.21	0.17	0.91
sort 6	0.84	0.96	89.97	-0.32	0.05	0.77
sort 7	0.69	0.83	101.41	-0.15	0.12	1.44
sort 8	0.91	0.37	40.81	0.67	0.06	0.83

Figure 8.9: **Cross-sectional average of fund expense ratio and expense ratio, 1976-2001.** The scale on left y-axis is for the turnover rate (in percentages per year) and the right y-axis is the expense ratio (in percentage per year).



portfolio about 5 years, while the average for the high turnover funds is 5 months. The average turnover for the whole sample is 95, indicating that each asset is traded about once per year. The relation between the turnover rates and expense ratios across groups is not immediately clear, but for the funds with lowest turnover, expense ratios are also lowest. This might be due to the lower transactions costs these funds are incurring by their infrequent trading behavior. The selectivity and expert timing returns of low and high turnover funds are higher than the average, 35 bp for the lowest turnover funds and 72 bp for the highest turnover funds. Wermers (2000), using a holdings-based decomposition, also finds that high turnover funds have higher average returns than low-turnover funds. He finds that funds with average turnover have the lowest selectivity as measured by the Carhart (1997) four-factor alpha. In contrast, Elton, Gruber, Das & Hlavka (1993) find that Jensen's alphas with respect to a three-factor model (market, small-cap, and bonds) are lower for funds with higher turnover or higher expense ratios.

We also rank the funds based on their expense ratio. Again, lowest expense ratios are associated with low turnover rates, but for the other groups the relation is less clear-cut. We see for this ranking, displayed in Panel B of Table 8.4, that management skill is highest for the group with highest average expenses. The second best performing group contains the funds with lowest expense ratio. Hence, as in the case with ranking on turnover, the average fund underperform the funds with more extreme expense ratios. In a Bayesian framework, Busse & Irvine (2002) model investor's prior beliefs about management skills to be centered around the negative of the expense ratio. Our results indicate that manager skills are positively related to expense ratios and hence provide evidence against investor's prior beliefs in the model of Busse & Irvine.

8.6 Conclusions

We investigate the investment performance of asset allocation mutual funds. In order to achieve this goal, we decompose the conditional expected return of the funds in five parts. Two of these, selectivity and expert timing, are related to management skill, and the other three capture time-variation in the market exposure. The model we use to estimate these components reduces to the well-known performance evaluation models of Lockwood & Kadiyala (1988) and Ferson & Schadt (1996) under certain restrictions. For several funds in our empirical investigation these existing models are restrictive. In some cases conclusions about the importance of selectivity and timing change once these restrictions are relaxed.

We determine the relative importance of these components by investigating a representative sample of 78 mutual funds with an asset allocation objective. Our results indicate that these funds vary their market exposure substantially over time. However, the cross-sectional expected return difference due to time-variation are small. The returns to market timing are absent on average, although some fund managers have significant timing ability. The negative correlation between selectivity and timing that is reported in this line of literature is also present in our results. This may be explained by option-like strategies that these fund managers employ. A portfolio with fund managers that perform well on selectivity and timing is therefore hard to construct by investors. Further, we find that there appears to be a common component in idiosyncratic fund returns, implying that these are also hard to diversify away for an investor.

We also investigate the relationship between turnover and expense ratios with the performance of these funds. We confirm the holdings-based results from Wermers (2000) that high and low turnover funds seem to have better manager skill. In addition, we also find that highest and lowest average expense ratios are indicative of better management skill.

Chapter 9

Conclusions

In Part I of this thesis, we analyzed stock return continuation in further detail. In the literature survey in Chapter 2, we indicated the different aspects of momentum investing and positioned our work from Chapters 3 and 4 in the existing literature. The lack of a widely accepted understanding of the phenomenon will probably keep the academic community in this field active in the coming years.

Our analysis in Chapter 3 focuses on industry momentum strategies. These strategies are designed to capture return continuation on the industry level by taking long (short) positions in industries with high (low) past returns. Our analysis contributes to the existing literature in several dimensions. First, we found that the industry momentum effect as documented by Moskowitz & Grinblatt (1999) for the US market, is robust with respect to the choice of industry classification scheme. This indicates that previously documented results are less likely to be caused by data-mining; the extensive data exploration to find apparent statistically significant relations. We find more evidence that the Japanese stock market is different as far as momentum is concerned, as an industry momentum effect is not be found in addition to studies that focus on individual stock return continuation in Japan (see, e.g., Chui, Titman & Wei 2001). Finally, we document that information about past industry performance across regions may improve trading strategies trying to exploit the industry momentum effect. For example, the European industry momentum effect is stronger on the one-year investment horizon when industries are ranked on the basis of the return of their US counterpart than the return of their own industry.

In recent years, the focus of investors in the European stock market has shifted from a country-based approach to an industry-based approach. We know that US momentum strategies are, at least partly, driven by industry momentum (see, e.g., Moskowitz & Grinblatt 1999), and that industry momentum is also present in the European market (see, e.g., Chapter 3). Several papers also document the existence of momentum at the country index level. We tried to answer the natural question that emerges: to which extent influence industry and country momentum the total momentum effect in Europe (see, e.g., Rouwenhorst 1998). We found that the total momentum effect is only partially influenced by country and industry momentum effects. This implies that asset managers who are reluctant to take large country or industry exposures may still be able to exploit stock return continuation in Europe. However, further research on trading costs for European equity markets, and momentum stocks in particular, should be conducted in order to determine whether these excess returns 'on paper' can be converted to real world excess returns.

We also investigate whether differences in stock characteristics, such as book-to-market ratio ("value") or market capitalization ("size"), influence the results on the influence of country and industry momementum. In order to achieve this goal, we extended the methodology of Heston & Rouwenhorst (1994) so that interaction-effects are taken into account. Our empirical results suggest that these non-linear effects are important when the value and size dimension are included in the analysis. We found that the momentum effect is stronger for firms with small market capitalization and growth characteristics. These empirical results can be seen as empirical evidence in support of the behavioral models of Hong & Stein (1999) and Daniel et al. (1998), who claim that firms with smaller information diffusion (proxied by small market capitalization) and firms that are harder to value (proxied by low book-to-market ratio) are more prone to exhibit momentum.

Future research in this area could try to explore the link between behavioral models and empirical data further. Specifically, the following topics seem to be promising. The influence of the institutional environment in which investors operate may influence their trading behavior. For example, Chui et al. (2001) investigate the effects of ownership structure and legal systems on the momentum effect in Asian countries. Grinblatt & Han (2002) analyze the effects of tax-loss selling on the seasonality documented in momentum returns. This type of analyses, linking investor motives to trade to observed return patterns, seem to be less emphasized in the existing literature. In addition, Barber & Odean (1999, 2001) and Grinblatt & Keloharju (2001) have recently tested several behavioral theories using individual trading data of the US and Finland, respectively.

A further analysis to the influence of classification schemes on the investment behavior by both institutional and private investors is motivated by Barberis & Shleifer (2003) and Barberis, Shleifer & Wurgler (2002). For example, industry reclassifications because of economic developments might impact results based on historical returns. A further investigation whether the new industry classification by MSCI for the European equity market influences the price or correlation of stocks could shed new light on behavioral explanations for institutional trading and the comovement of stock prices in particular.

In Part II of this thesis, we analyze the asset allocation of pension funds. In Chapter 5, we conclude that imminent regulatory changes direct Dutch pension funds to invest more in government bonds. The most important reasons we put forward for this development are (a) the more explicit hedge of pension fund liabilities by bonds when liabilities are valued according to market value, (b) the company's desire to hedge pension risk arising from new international accounting standards, and (c) the more strict assumption on the expected returns of stocks relative to that of bonds compared to their historical averages that are frequently used. We further indicate that a higher weight of bonds in the institutional portfolio implies higher contribution rates or less generous pension schemes.

In Chapter 6 we further analyze the benefits of investing in the alternative asset class commodities for investors with liabilities (see, e.g., Bodie (1980)). We found that commodities shift the mean-variance frontier significantly outward for mean-variance investors with inflation-indexed liabilities, but not for investors with nominal liabilities. Thus, our results suggest that commodities are a good hedge against risks in US inflation-indexed liability returns, and allocation of part of the pension fund portfolio to commodities reduces the volatility of the funding ratio. Our results indicate that the current debate in Europe to restrict pension funds in their investment opportunities to derivatives and alternative assets might increase rather than decrease the riskiness of pension funds. A professional and prudent use of these assets could decrease the probability that a pension scheme becomes insolvent.

The modeling of the real term structure is of major importance for the valuation of liabilities and hence the asset allocation of pension funds. The lack of inflation-linked assets makes it hard to find investment opportunities that are good hedges against the returns of the pension liabilities. Optimal asset allocation depends crucially on the structure of the funds and a correct assessment of liability value is important for asset allocation, risk management, and appropriate supervision; see, e.g., Blake (2001) for a study on the changes in the pension fund regulation in the United Kingdom.

The research in this area may prove to be fruitful in several directions. We focused on a pension fund with mean-variance utility function in Chapters 5 and 6, but optimal asset allocation for investors with constraints, should for example incorporate the probability of underfunding. More research on this topic is relevant for pension fund managers to determine the optimal asset allocation, especially in a dynamic context.

Also of interest to the pension fund industry is how to adequately supervise the pension fund industry in The Netherlands or in the European Community. The new Financial Assessment Framework in The Netherlands is still under development, and results on optimal design and implementation are relevant for companies that offer a pension scheme, but also for the employees who save part of their salaries now for consumption in the (distant) future. A deeper understanding of the trade-off between long-term risks and rewards and short-term risk management is essential to establish a fruitful environment in which pensions can be provided at a reasonable price.

Part III of this thesis contributes to the literature on mutual fund style analysis (see, e.g., Sharpe 1992) and timing performance evaluation (see, e.g., Treynor & Mazuy 1966). In Chapter 7 we analyzed the suboptimal use of rolling window OLS estimators for dynamic exposures in returns-based mutual fund style analysis. We showed that in three stylized examples a Kalman filter approach outperforms the rolling window estimation substantially. In an empirical investigation of the exposures of US-based international mutual funds the Kalman filter approach also outperforms the rolling window estimator, but the magnitude of gains in economic terms is somewhat reduced. Recently, Spiegel et al. (2003) use a similar approach and find that the use of alphas and betas estimated by the Kalman filter improve trading strategies relative to trading strategies based on alphas and betas based on OLS estimation.

In Chapter 8 we analyzed the dynamic investment behavior of mutual funds with an asset allocation perspective. We found only limited empirical evidence in favor of timing ability, i.e., the managers of these funds do not seem to be able to increase (decrease) their exposure to the stock market when the returns are relatively high (low). Furthermore, we also find that only a small part of the dispersion in mutual fund returns can be attributed to market timing. This indicates that the timing ability of managers does not account for the difference in average returns of asset allocation funds. Our analysis indicates that asset allocation funds with high turnover and high expense ratios are associated with fund management with higher (selectivity and timing) ability. While results on the influence of trading activity and performance are unambiguous, our results are in line with recent work by Wermers (2000). More research on the relation between trading activity and investment performance could enrich the literature in this research area further.

The research in the area of performance evaluation of mutual fund managers has taken different routes. The return based perspective, which we take in our analyses, makes use of net asset values at a monthly frequency, although recently several attempts have been made to use returns on a day-by-day basis (see, e.g., Bollen & Busse 2001). The holdings-based perspective makes use of the actual portfolio composition of mutual funds (see, e.g., Wermers 2000). When holdings are used, more precise portfolio information can be used to analyze the performance of the manager. The disadvantage of this approach is the low frequency on which these holdings are available for the investment public, and potential window dressing activities of fund managers. Furture research in this field could improve performance evaluation analyses by incorporating high-frequency fund returns and low frequency fund holdings. In addition, taking into account changes in fund management and/or fund objective (see, e.g., Khorana 2001) could give more detailed information about future performance of the mutual fund.

Nederlandse Samenvatting

Dit proefschrift bestaat uit drie delen. In het eerste gedeelte staat een bepaald soort aandelenstrategie centraal. Deze zogeheten momentum strategieen zijn gebaseerd op het empirische fenomeen dat aandelen die in de afgelopen zes maanden een relatief hoog rendement hebben behaald het komende half jaar wederom een relatief hoog rendement ten opzichte van andere aandelen laten zien. Dit type strategie heeft het laatste decennium veel aandacht gekregen in de academische literatuur, voornamelijk vanwege het gebrek aan een rationele verklaring die door geobserveerde data wordt gesteund. In Hoofdstuk 2 geven we een overzicht van de academische literatuur op dit gebied. Hierin wordt onder andere een vergelijking gemaakt tussen empirische bevindingen, waarbij verschillen in onderzoeksmethodologie verder geanalyseerd worden. Verder worden een aantal verklaringen voor het bestaan van exces rendementen op deze strategieen beschreven. Zowel de stroming die beargumenteert dat het exces rendement een compensatie voor risico is als de stroming die de psychologie van de belegger probeert te doorgronden komen hierbij aan bod. Een aantal recente onderzoeken beweert echter dat transactie-kosten die deze momentum strategieen met zich mee brengen groter zijn dan het te verwachten exces rendement, waardoor wordt gesuggereerd dat implementatie door grote institutionele beleggers niet zinvol is.

In Hoofdstuk 3 en 4 bouwen we voort op Moskowitz en Grinblatt (1999), die voor een specifieke sectorindeling laten zien dat het bovengenoemde momentum effect geheel kan worden verklaard door momentum op sector-niveau. Dit impliceert dat geen momentum effect aanwezig is in een beleggingsportefeuille waarbij sector-specifieke risico's geelimineerd worden. In Hoofdstuk 3 laten we zien dat voor een andere indeling van aandelen in economische sectoren de gevonden resultaten sterk lijken op die van Moskowitz en Grinblatt (1999). We vinden dat in de Europese aandelenmarkt ook sectormomentum aanwezig is. Op de Japanse markt is dit echter niet het geval. We onderzoeken ook of het relatieve rendement van een sector in een van drie bovengenoemde regio's voorspellende waarde heeft voor de relatieve performance van die sector in een andere regio. We vinden dat de momentum strategie in Europa een hoger verwacht exces rendement heeft wanneer geselecteerd wordt op het historische rendement van de Amerikaanse sector in plaats van de Europese sector. We vinden ook, zij het in mindere mate, een dergelijk verband tussen Europa en Azie.

In Hoofdstuk 4 maken we een decompositie van het rendement op Europese momentum strategieen. De centrale vraag die in dit hoofdstuk gesteld wordt is of het momentum effect in Europa ook verklaard kan worden door momentum op sector niveau (Moskowitz en Grinblatt 1999) of door momentum op landen niveau (Chan et al. 2000). Om dit te onderzoeken maken we gebruik van een regressie-techniek waardoor we expliciet kunnen toetsen of kruiseffecten tussen landen en sectoren een belangrijke rol spelen. Dit is een uitbreiding op het model van Heston en Rouwenhorst (1994). Onze resultaten wijzen erop dat het individuele effect in aandelen het grootste gedeelte van het momentum effect verklaard over de periode 1990-2001. Een relatief klein gedeelte kan worden toegeschreven aan sector momentum, terwijl vrijwel geen momentum op land niveau lijkt te bestaan. Deze conclusies zijn niet gevoelig voor het introduceren van de effecten gebaseerd op de marktkapitalisatie of boekwaarde/marktwaarde van aandelen. We vinden wel dat kruiseffecten in deze analyse belangrijk zijn. Het momentum effect is in onze analyse het sterkste voor aandelen met een relatief lage boekwaarde/marktwaarde en kleine marktkapitalisatie.

In het tweede gedeelte van dit proefschrift worden twee hoofdstukken gewijd aan het beleggingsbeleid van pensioenfondsen. In Hoofdstuk 5 wordt nader ingegaan op de situatie voor pensioenfondsen in Nederland, en dan met name de invloed van de veranderingen in de regelgeving. Er zijn een aantal belangrijkste veranderingen die - al dan niet in concept-vorm - door de Pensioen- en Verzekeringskamer zijn gepubliceerd. De belangrijkste omslag is het gebruik van de marktwaarde van pensioenverplichtingen in plaats van actuariele waardering. De hoogte van de vereiste financiele buffers zal afgeleid worden van de mismatch tussen de bezittingen en verplichtingen van het pensioenfonds in kwestie. Deze beoogde regelgeving bevat prikkels om meer in vastrentende waarden te beleggen dan nu het geval is. Daar komt nog eens bij dat nationale en internationale boekhoudregels vereisen dat het rendement van het pensioenfonds op de balans of resultaatrekening van de sponsor tot uitdrukking wordt gebracht. Risicoreductie door meer in obligaties te beleggen zal vanuit de onderneming waarschijnlijk dus ook voorgestaan worden.

In Hoofdstuk 6 wordt onderzocht of pensioenfondsen er verstandig aan doen om in de alternatieve activaklasse commodities te beleggen. Dit is zowel een relevante vraag voor beleggers als voor regelgevers, die in Europees verband zeer terughoudend zijn als het gaat om toelaten van alternatieve beleggingen in portefeuilles van pensioenfondsen. Er worden twee typen verplichtingen nader onderzocht: nominale verplichtingen en tegen inflatie-beschermde verplichtingen. We maken gebruik van een spanning toets om formeel vast te kunnen stellen of beleggen in commodities een significante verbetering van de mean-variance grenslijn oplevert indien het fonds reeds in obligaties en aandelen belegt. Uit onze analyse blijkt dat door toevoeging van commodities als beleggingsklasse een significante verbetering optreedt indien de pensioenverplichtingen een inflatie-bescherming kennen, terwijl dit niet het geval is voor niet geindexeerde ofwel nominale aanspraken. We trekken deze conclusie voor zowel een strategische (3-jaars) als een korte (3-maands) beleggingshorizon. Indien we echter gebruik maken van kennis over de huidige economische situatie, dan blijkt dat het ook voor een pensioenfonds met nominale verplichtingen soms optimaal is om in commodities te beleggen. Verder vinden we dat tactische allocatie tussen commodities en aandelen toegevoegde waarde kan hebben vanuit een strategisch oogpunt. Deze analyse wijst erop dat al te stringente regelgeving ten aanzien van alternatieve beleggingen niet in het voordeel is van de pensioengerechtigden, mits er sprake is van bekwaam pensioenfondsbestuur.

Het derde deel van dit proefschrift bestaat eveneens uit twee hoofdstukken. Hierin wordt het beleid van beleggingsfondsen nader onderzocht. In Hoofdstuk 7 wordt een manier gepresenteerd om de beleggingsstijl van een fonds te schatten en in Hoofdstuk 8 wordt onderzocht in hoeverre beleggingsfondsen in staat zijn te voorspellen of de aandelenmarkt gaat stijgen of dalen.

In Hoofdstuk 7 wordt een methode om de stijl van beleggingsfondsen te schatten door enkel gebruik te maken van fonds- en indexrendementen nader onderzocht. Meer specifiek wordt ingegaan op de manier waarop een dynamische beleggingsstijl geschat kan worden. In deze literatuur is het standaard om gebruik te maken van een rolling window schatter. Deze veelgebruikte schatter is echter niet gebaseerd op statistische theorie en vereist een subjectieve keuze van de lengte van de window. In dit paper stellen wij voor om bij dynamische stijlanalyse gebruik te maken van het Kalman filter. Deze schattingsmethode maakt gebruik van een expliciet model voor de dynamiek in coefficienten en is statistisch onderbouwd. Uit een aantal gestileerde voorbeelden blijkt dat de door ons voorgestelde schatter betere resultaten geeft dan de standaard methode. We passen beide methodes ook toe op voorbeelden uit de praktijk. Voor Amerikaanse beleggingsfondsen met een internationale beleggingsstijl blijkt dat performance maatstaven substantieel kunnen wijzigen indien rekening gehouden wordt met dynamische stijlen.

In Hoofdstuk 8 wordt gebruik gemaakt van de schattingstechniek in Hoofdstuk 7 om de performance van beleggingsfondsen met een dynamische allocatie tussen kasgeld en de aandelenmarkt te onderzoeken. We maken een decompositie van het rendement van beleggingsfondsen en analyseren welke componenten de grootste invloed hebben op het rendement. We maken hierbij onderscheid tussen de bekwaamheid van de managers en componenten die een particuliere belegger ook zelf zou kunnen nabootsen. De bekwaamheid van de manager wordt uitgeplitst naar timing (het vergroten van de marktpositie als die gaat stijgen) en selectiviteit (het selecteren van de juiste aandelen in de markt). Een belangrijke conclusie hierbij is dat timing (het goed voorspellen van periodes dat aandelenmarkten het goed doen) slechts een beperkte invloed heeft op het verwacht rendement van de meeste fondsen. Verder blijkt dat de meerderheid van de fondsen niet in staat is om de richting van de markt consistent goed te voorspellen. Een beperkt aantal fondsen heeft echter wel significant positieve resultaten geboekt. Het is echter lastig voor beleggers om hiervan te profiteren, aangezien positieve timing vaak gepaard gaat met negatieve selectiviteit. Onze analyse geeft tevens aan dat fondsen met een hoge kostenvoet en fondsmanagers die veel handelen geassocieerd worden met abnormaal positieve bekwaamheid.

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