DAVID BLITZ

Benchmarking Benchmarks

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Benchmarken van Benchmarks

THESIS

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Preface

So, at long last, I did it. In the eyes of many, this PhD thesis is long overdue. But back in 1995, when I had completed my masters in econometrics, the prospect of becoming an ‘aio’ and spending four years on writing a PhD thesis did not appeal to me at all. I had just finished my theoretical master’s thesis, on a topic in discrete mathematics which interested only a handful of people in the entire world. The experience consisted of sitting alone in a room for six months, racking my brain and concluding time and again that none of my ideas worked. Although in the end I managed to slightly improve a result in the PhD thesis of my supervisor, André van Vliet, who happened to be so excited by this that he graded my master’s thesis with a straight 10, I had learned that this was not the road to happiness for me. So when Angelien Kemna from IRIS Quantitative Research invited me for a chat about a job opening in her team, I did not need to think very long. I never regretted the decision to pursue a career in quantitative asset management, initially at IRIS and later at Robeco, as this must surely be one of the most exciting and challenging research areas. It is not an easy job though, because a model that fits the past perfectly may turn out to be utterly useless subsequently. As financial markets keep on evolving, so should financial researchers and their work.

So what inspired me to start working on a PhD thesis after all? First of all, Peter Ferket, who was my boss from 2000 until 2007. For a long time I ignored his mocking remarks that I had only finished the first half of a proper academic education and still needed to complete the second half. He finally managed to convince me by arguing that in order to become an authority in quantitative research, it is necessary to either become a CFA charter holder or write a PhD thesis. As CFA sounded quite boring to me (and still does), this meant that there was really only one option for me. Peter, I would like to thank you for the inspiration that you have been to me.

The second motivation came from the fact that, over the years, an increasing number of PhD’s joined our team, who brought along a lot of valuable practical experience with writing academic papers, and who liked to keep on writing papers occasionally. All chapters in this PhD thesis are in fact based on papers written together with my colleagues Pim van Vliet, Laurens Swinkels, Joop Huij and Martin Martens. Guys, I want to sincerely thank you for sharing your experience with me and the fruitful results of our cooperation. Pim, I like writing papers with you because your skills are so complimentary to mine. Laurens, I like to thank you in particular for taking the initiative to approach Angelien Kemna which actually set this thesis in motion. Joop, I admire the apparent ease with which you can write papers which land in quality journals. And, finally, Martin, you are just incredibly intelligent. I would also like to thank Robeco for allowing me to spend part of my working time on writing this thesis.

A special word of thanks goes to my promotors, Angelien Kemna and Willem Verschoor. Angelien, thank you for your trust and support as my promotor. I particularly admire your plainspoken and candid communication style. Willem, thank you for your valuable input and pro-active approach.

Last but not least I want to thank my family for supporting me throughout this endeavor. Pauline, for taking care of the kids so often. Bob, for showing me true fighting spirit. And, finally, my little sweethearts, Nina and Jet.

David Blitz
Rotterdam, March 2011

Contents

1 Introduction

1.1 Benchmarking

Suppose you invested in an equity mutual fund which delivered a return of 10% over the past year. Are you satisfied with this performance? The answer depends. If you compare the performance of your fund to a savings account which returned 4% over the same period, you might conclude that you made a good investment decision. But you are probably less satisfied with the performance of your fund if you observe that comparable equity mutual funds delivered an average return of 25%, as this suggests that there was plenty of opportunity for your fund to produce a return well above 10%. Likewise, if a pension fund generated a return of 10% on its assets, more information is required in order to assess whether or not the fund did a good job. In order to determine if the financial health of the fund has improved or deteriorated, the return on the assets of the fund should be compared to the change in the value of the liabilities of the fund over the same period. These simple examples show that investing is not simply about generating good returns in an absolute sense, but also about returns relative to some reference point, or benchmark.

The importance of relative performance can be illustrated by considering the mutual fund market. With thousands of mutual funds being offered for sale, fund managers operate in a highly competitive environment. Research has shown that cash-flows into and out of mutual funds are strongly related to the performance of funds relative to their peer group.[1] Websites such as Morningstar.com enable users to quickly make such peer group comparisons. Switching between mutual funds from competing providers has become increasingly easy as well. Whereas in the past many European banks only offered mutual funds from their own asset management division, many have now adopted an 'open architecture' policy in which funds from various competing providers are offered to end-investors. As a result of these developments, good relative performance has become essential for the survival of a mutual fund.

Peer group performance comparisons may be well suited for *ex post* benchmarking purposes, but *ex ante* a fund manager does not have information on the

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[1] Sirri and Tufano (1998) report that consumers base their fund purchase decisions on prior performance information, but do so asymmetrically, investing disproportionately more in funds that performed very well the prior period.

holdings of competing funds[2], so a different approach is needed. The market portfolio, in which all stocks are weighted according to their market capitalization, constitutes a good alternative which does not suffer from this drawback. As the market portfolio contains all the shares that are outstanding in a certain market, it effectively represents the collective holdings of all investors active in that market. Loosely speaking the market portfolio can therefore be interpreted as the portfolio of the 'average' investor. In practice the market portfolio is approximated by capitalization-weighted indexes, such as the S&P 500 index which represents the U.S. (large-cap) equity market. Benchmarking funds to indexes has become very popular. In fact, it has become common practice for a fund to explicitly refer to a specific benchmark index which may be considered representative for its investment activities, and which can be used to evaluate the performance of the fund *ex post*.

People respond to incentives, so if fund managers know that they will be evaluated against some pre-specified benchmark index, they will concentrate their efforts on outperforming (doing better than) that index. Gone are the days when investors might have been satisfied with a fund with a decent absolute return of 10%, when over the same period the benchmark index actually delivered a return of 25%. With 15% underperformance the fund manager should in fact worry about keeping his job. Investing has thus become a relative game, where the main focus is on beating the market, in other words, to outsmart the average investor. In this environment the main risk is no longer the possibility of a decline in the absolute value of the portfolio, but the possibility of a return lower than that of the benchmark index, or underperformance. This suggests a potential conflict of interest. Whereas the absolute return and risk of a fund are still what ultimately matters to end-investors, fund managers are primarily concerned with relative (or active) return and risk instead.

Among these end-investors are institutional investors such as pension funds. As institutional investors tend to face a certain liability stream, their investment approach has evolved into a two-stage hierarchical process. In the first stage of the hierarchy a benchmark strategic allocation over asset classes is determined. The strategic asset allocation, or SAA, consists of target weights for each asset class, such as equities, bonds and real estate. In order to determine the SAA policy, institutions usually conduct an Asset Liability Management (ALM) study, in which the strategic investment policy, funding policy and indexation policy are integrally analyzed in conjunction with the institutions' future liabilities. In this stage the absolute risk and return properties of the various asset

[2] Detailed holdings information is typically provided with a low frequency and a considerable publication lag.

class and the liabilities are of primary concern. The next stage consists of selecting fund managers for managing the various parts of the portfolio. In addition, tactical asset allocation (TAA) might be employed: dynamically adjusting the weight of asset classes based on short-term risk/return considerations. In this stage the focus shifts to performance relative to the benchmark SAA portfolio.

Outperforming the market average has become the name of the game of the professional asset management industry, but it is not an easy objective. Numerous studies have shown that the majority of professional fund managers fail to outperform their benchmarks. This is not really surprising in light of the facts that (i) collectively professional fund managers constitute most of the market, and (ii) investing is a zero-sum game before costs, and a negative-sum game after costs. This realization has been one of the main drivers behind the rise of passive investing, where the objective is to simply replicate a benchmark index at minimal costs. In recent years passive investing was given an additional boost with the introduction of so-called Exchange Traded Funds, or ETFs, which replicate popular indexes and can be traded throughout the day, very similar to individual stocks. Despite the growing popularity of passive management, active management remains the dominant investment approach. In fact, it can be argued that the larger the market share of passive management, the less efficient the market will become, and therefore the stronger the case for active management. And whereas everyone can be an active investor, it is hard to imagine a world with only passive investors, as active investment is essential for price discovery and efficiently functioning capital markets.

Benchmarking is an intriguing phenomenon and the common theme throughout this thesis. In section 1.2 we examine the role of benchmarking in finance more formally, by putting it in the context of the academic literature on this subject. Inspired by the ever-growing importance of benchmarking we continue by formulating the central research questions of this thesis. These can be found in section 1.3, together with a brief summary of our main results, i.e. the insights which are provided by this thesis. In section 1.4 we outline the remainder of the thesis.

1.2 Academic setting

In the nineteen sixties the Capital Asset Pricing Model (or CAPM)[3] was developed, which lies at the foundation of modern finance theory. The CAPM states that the expected return

[3] The CAPM was developed by Treynor (1961, 1962), Sharpe (1964), Lintner (1965a,b) and Mossin (1966) independently, building upon the Markowitz (1952) paper on diversification and modern

on a stock in excess of the risk free rate of return is proportional to its systematic risk, measured by its beta with respect to the market portfolio:

$$(1.1) \qquad E(r_i) = r_f + \beta_i\,[E(r_m) - r_f]$$

where

$E(r_i)$: expected return on stock i
$E(r_m)$: expected return on the market portfolio
r_f : risk free rate of return
β_i : beta of stock i with regard to the market portfolio, equal to $\mathrm{cov}(r_i,r_m)/\mathrm{var}(r_m)$

In the nineteen seventies the CAPM was generalized into the Arbitrage Pricing Theory (or APT)[4], which postulates that the expected return of a stock is a linear function of its exposures to an (unspecified) set of systematic risk factors. In other words, the APT recognizes that market beta may not be the only systematic risk factor driving stock returns. Contrary to the CAPM, the APT is basically untestable, as the relevant systematic risk factors are not explicitly defined. What the CAPM and APT models have in common is that both state that the expected return to idiosyncratic risk, i.e. diversifiable stock-specific/non-systematic risk, is zero.

Alpha is defined as the return of a stock (or portfolio of stocks) after adjusting for its systematic exposures, such as market beta in the CAPM:

$$(1.2) \qquad \alpha_i = (r_i - r_f) - \beta_i\,(r_m - r_f)$$

The Efficient Markets Hypothesis (or EMH)[5], which was inspired by the CAPM, basically states that no investment strategy should be able to generate a consistently positive alpha.[6] Although some of the earliest tests of the CAPM already indicated that the empirical data did not neatly fit with the theory[7], the EMH theory was widely accepted up until the nineteen nineties. By then an increasing number of studies began to appear, which challenged the EMH, by presenting empirical evidence that various relatively simple

portfolio theory. Sharpe, Markowitz and Merton Miller jointly received the Nobel Memorial Prize in Economics for this contribution to the field of financial economics.
[4] See Ross (1976).
[5] See Fama (1970).
[6] Except when acting upon inside information - which is illegal in most countries.
[7] See chapter 3 for more details.

investment strategies do appear to be associated with highly significant positive alphas historically. The best known examples are the size effect[8] (small stocks, in terms of market capitalization, outperform large stocks), the value effect[9] (cheap stocks, e.g. in terms of the book value-to-market capitalization ratio, outperform expensive stocks) and the momentum effect[10] (stocks with high past returns outperform stocks with low past returns). Some interpret these anomalies as evidence of systematic market inefficiencies which arise because of behavioral biases of investors (i.e. true alphas)[11], while others argue that they represent priced risk factors in the spirit of the APT (i.e. additional betas)[12]. Based on the latter reasoning, the Fama-French 3-factor asset pricing model[13] (with market beta, size and value factors) and the Carhart 4-factor model[14] (same plus momentum factor) were introduced. These models can be seen as practical applications of the theoretical APT model.

Regardless of how one interprets the size, value and momentum effects, the CAPM, 3-factor and 4-factor models have become widely accepted benchmarks for academic asset pricing research. On the Kenneth French website[15] long-term historical data for the market, size, value and momentum effects is maintained and available free of charge to anyone interested, which has undoubtedly contributed to the popularity of these series as benchmarks in academic research. Nowadays, it is common practice for an academic researcher, who finds a certain cross-sectional return irregularity, to first investigate to which extent the alpha remains after adjusting for known betas, i.e. loadings on the already known effects in the benchmark CAPM, 3-factor and 4-factor models.

1.3 Main research questions and findings

The central research questions of this thesis are inspired by the prevalence of benchmarking in academic research as well as in investment practice. Amongst others, we investigate if popular benchmarks are appropriate, if alpha in excess of benchmark returns

[8] See Banz (1981).
[9] See Stattman (1980) and Rosenberg, Reid and Lanstein (1985).
[10] See Jegadeesh and Titman (1993).
[11] Lakonishok, Shleifer and Vishny (1994) argue that the outperformance of value stocks arises because investors systematically underestimate the earnings growth prospects of such stocks. Chan, Jegadeesh and Lakonishok (1996) argue that the momentum effect is due to the market's underreaction to information, in particular to past earnings news.
[12] For example Fama and French (1996).
[13] See Fama and French (1992).
[14] See Carhart (1997).
[15] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

can be obtained, and if benchmark returns are actually attainable in practice. These questions are highly relevant from a theoretical as well as from a practical perspective. In the following subsections we describe and motivate the specific research questions in detail. We also briefly summarize our key findings, i.e. the answers that are provided by the studies in the following chapters of this thesis.

1.3.1 Is there alpha in the equity market?

Our first central research question is whether there is alpha in the equity market, i.e. returns which are not explained by the current benchmark asset pricing models as described in the previous section. In case the answer to this question is affirmative, this has important theoretical and practical implications. Theoretically, the finding of economically and statistically significant alphas, which cannot be explained by current benchmark asset pricing models, suggests that these models are inadequate for a proper understanding of the cross-section of stock returns. Evidence of alpha opportunities is also highly relevant for practitioners, as it may indicate a way in which outperformance relative to the benchmark could be generated.

Many studies of the cross-section of stock returns claim to find alpha which cannot be explained by benchmark asset pricing models such as the CAPM, 3-factor and 4-factor model. In a recent study, Fama and French (2008) put some of the most promising new contenders to the test, but conclude that there is no strong case for abandoning or modifying the existing asset pricing models.[16] To date, the CAPM, 3-factor and 4-factor models remain the generally excepted benchmark for cross-sectional asset pricing studies. But is there really little or no alpha beyond these, by now classic, asset pricing models? Three studies in this thesis relate to this question.

In our first study we examine momentum strategies.[17] We show that the benchmark momentum factor in the 4-factor model vastly underestimates the true potential of momentum strategies, because an alternative momentum strategy exhibits risk-adjusted profits that are about double those of traditional momentum strategies. In our second study we document a strong return irregularity which is not captured by the CAPM, 3-factor and 4-factor model.[18] Our main finding is that stocks which exhibit a low (high) past volatility

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[16] The asset growth anomaly and the profitability anomaly turn out not to be very robust, while the alpha of the net stock issuance anomaly and the accruals anomaly appears to be limited to the extremes.

[17] This study is based on Blitz, Huij and Martens (2009).

[18] This chapter is based on Blitz and van Vliet (2007).

earn abnormally high (low) risk-adjusted returns subsequently. In our third study we critically examine recently proposed fundamental benchmark indexes, in which stock weights are based on company fundamentals such as book value instead of market capitalization.[19] We show that fundamental indexation is not a revolutionary concept, but simply an elegant new way to capture the classic value premium.

1.3.2 Is there alpha in the asset allocation space?

Our first central research question concerned the cross-section of stock returns. For our second central question we shift our perspective to asset allocation, which concerns entire asset classes, such as equities and bonds. The question is similar though: can active asset allocation add value over a benchmark strategic asset allocation (SAA) portfolio? In practice, strategic asset allocation often turns into static asset allocation, i.e. a mix of betas that is held constant over time. As the asset allocation decision has been shown to be the main determinant of investors' end-returns, it is important to know if a more active approach towards asset allocation may provide added value.

One stream of literature shows that active asset allocation strategies may exploit effects similar to those that are known to exist within the cross-section of stock returns. For example, for equity country allocation both medium term momentum and long-term mean-reversion have been shown to be effective, see Chan et al. (2000) and Richards (1995, 1997). Another example are carry strategies for currencies, as documented by Hodrick (1987) and Froot and Thaler (1990), which may be interpreted as value strategies. In practice tactical asset allocation (TAA) strategies have become popular, which basically consist of a combination of several such strategies, implemented by means of a derivatives overlay. However, a direct comparison of a broad range of asset classes is typically not made in TAA programs, perhaps because the literature also remains largely silent on this topic.

Our first asset allocation study intends to fill this gap in the literature by examining if value and momentum effects, which are known to exist within many asset classes, can also be observed across entire asset classes.[20] We find that this is indeed the case, and that although these effects are positively related to the Fama-French value and Carhart momentum factors, they do in fact constitute distinct return irregularities.

[19] This chapter is based on Blitz and Swinkels (2008).
[20] This chapter is based on Blitz and van Vliet (2008).

Another stream of literature documents that variables which are related to the business cycle, such as the term spread, credit spread and dividend yield, predict time-variation in the expected return of asset classes such as equities. However, it is not obvious how these insights may be turned into a practically feasible investment strategy. Furthermore, such a strategy should not only consider the time-varying return, but also the time-varying risk characteristics of asset classes. Markov regime-switching models, which are the subject of yet another stream of literature, do explicitly identify two or more regimes which capture time-variation in the expected return, as well as risk, of an asset class. The complexity of this approach constitutes an important practical drawback though. As a result of this practitioners tend to be reluctant to rely on the predictions of Markov regime-switching models. What is lacking therefore, is an active asset allocation strategy which stabilizes risk and optimizes return over the business cycle, and which satisfies important practical criteria such as transparency and consistency with practitioner's intuition.

In our second asset allocation study we address this need by proposing a dynamic strategic asset allocation (DSAA) approach which stabilizes risk across the economic cycle and which has the potential to enhance expected return as well.[21] Contrary to a purely statistical approach based on Markov regime models, our DSAA approach is centered around a transparent economic business cycle classification model, which uses four well-known economic indicators to identify four phases in the economic cycle. Our proposed approach can help investors to bridge the gap between long-term SAA and short-term TAA in practice.

1.3.3 Can benchmark index returns actually be obtained in reality?

The benchmarking of active fund managers has made clear that many, in fact the majority, of active managers fail to outperform their benchmark indexes. As mentioned before, this is not particularly surprising in light of the fact that active management is a zero-sum game before costs and a negative-sum game after costs. This realization has contributed to the growing popularity of passive investing, i.e. to simply follow a benchmark index as closely as possible and at minimal costs. In many studies it is either explicitly or implicitly assumed that cheap passive exposure to (a good proxy for) the market portfolio is a realistic alternative to active investment strategies. For example, the SPDR (pronounced: spider) on the S&P 500 index has been shown to successfully replicate the index against

[21] This chapter is based on Blitz and van Vliet (2009).

minimal costs, see Elton et al (2002). Most of this literature concerns the U.S. market though. This brings us to our third and final central research question, namely whether it is safe to assume in general that paper indexes constitute a fair benchmark, based on the notion that an investor should be able to simply replicate the return of an index by buying and holding the index portfolio.

In order to answer this question we examine the performance of passive funds listed in Europe in comparison to their benchmark indexes.[22] Our results show that the passive funds in our sample lag their benchmarks by a statistically and economically significant amount of 50-150 basis points per annum as a result of expenses and dividend taxation. This suggests that the paper returns of standard indexes, which neither take into account expenses nor the impact of dividend withholding taxes, are not attainable for European investors in reality and therefore not an appropriate benchmark for actively managed funds.

1.4 Outline

The remainder of this thesis is organized as follows. The six studies mentioned in the previous section can be found in chapters 2 to 7. Chapter 2 contains our research on momentum within the cross-section of stock returns. In chapter 3 we show that benchmark asset pricing models fail to explain the return of portfolios that are based on sorting stocks on their past volatility. In chapter 4 we discuss the recently proposed fundamental indexing approach. In chapter 5 we examine value and momentum effects at the level of asset classes and in chapter 6 we present our dynamic strategic asset allocation framework. Finally, we analyze the performance of passive funds listed in Europe in chapter 7. We note that because each chapter is basically a self-contained study, the chapters can also be read in isolation or in a different order.

In chapter 8 we conclude. We first summarize the main findings in this thesis. Next, we look at the results with a 'helicopter view' and try to deduce some more general insights and implications regarding the phenomenon of benchmarking. In particular, we argue that it could be benchmarking itself which lies at the root of some of our key findings. We elaborate on this idea and raise the question what investors should do to avoid the pitfalls associated with benchmarking, or even turn these insights to their advantage.

[22] This chapter is based on Blitz, Huij and Swinkels (2009).

2 Residual Momentum[1]

2.1 Introduction

Conventional momentum strategies, as described in the seminal work of Jegadeesh and Titman (1993; 2001), are based on total stock returns. In this study we investigate in detail a momentum strategy based on residual returns estimated using the Fama and French three-factor model. Our main contribution is to show that residual momentum poses a much more serious threat to market efficiency than total return momentum. The Sharpe ratio of residual momentum, for example, is approximately double that of total return momentum, mainly due to much lower return variability. The reason is that momentum has substantial time-varying exposures to the Fama and French factors, as illustrated by Grundy and Martin (2001). Specifically, momentum loads positively (negatively) on a factor when this factor has a positive (negative) return during the formation period of the momentum strategy. By design residual momentum has much lower time-varying factor exposures.

Residual momentum does not only improve upon total return momentum in terms of long-term average Sharpe ratios, but also in many other ways. These features allow us to rule out the key arguments that have been put forward in the academic literature over the past years to rationalize momentum.

First, a variety of papers argue that momentum displays characteristics that are often associated with priced risk factors. Chordia and Shivakumar (2002), for example, report that the profits of momentum strategies exhibit strong variation across the business cycle. Most notably, the profits of momentum strategies are generally negative during economic contractions, averaging –9.2 percent per annum in the second half of recessionary periods as defined by the National Bureau of Economic Research (NBER). Residual momentum, on the other hand, exhibits markedly different behaviour, delivering significantly positive returns during both economic expansions and contractions, including an average return of 9.6 percent per annum in the second half of recessionary periods.

Second, another risk-based explanation is that momentum trading strategies are concentrated in the highest credit-risk firms that are more likely to suffer financial distress, as illustrated by Agarwal and Taffler (2008), and Avramov et al. (2007). Consistent with these results, we find that total return momentum is concentrated in small cap stocks with

[1] This chapter is based on Blitz, Huij and Martens (2009).

above average betas and high levels of firm-specific risk. Residual momentum, however, does not appear to be tilted towards a specific market segment of the equity market and is also observed among large cap stocks with lower levels of firm-specific risk

A third critical view on the momentum anomaly is based on transaction costs and turnover. Lesmond et al. (2004), and Korajczyk and Sadka (2006) argue that momentum profits are difficult to capture because momentum strategies require frequent rebalancing and are concentrated in small cap stocks that typically involve large transaction costs. However, this critique does not apply to residual momentum, as we find significant and large risk-adjusted returns of 4.7 percent per annum when restricting the universe to large caps and considering a holding period of one year.

Finally it is interesting to note that, following the publication of a large number of academic studies on the momentum anomaly in the nineties, total return momentum has an insignificant average return of only 0.35 percent per annum over the period January 2000 to December 2007. Hence, the Adaptive Market Hypothesis of Lo (2004) seems to apply. This hypothesis states that the public dissemination of an anomaly will affect its profitability. We conjecture that it could well be the case that increased investment activities by professional investors such as hedge funds has arbitraged away a large portion of the anomalous profits of conventional total return momentum strategies. Interestingly, residual momentum yields a significant return of 12.78 percent per annum from 2000 to 2007, and hence remains remarkably robust over the most recent time period.

Our work extends the research by Grundy and Martin (2001) who show that momentum has dynamic exposures to the Fama and French factors. The authors find a significantly improved performance for a hypothetical strategy which hedges these exposures by taking positions in zero-cost hedge portfolios using hindsight estimates of factor exposures. However, when they evaluate a feasible strategy which uses information that is available *ex ante* they only find a marginal improvement in performance. The residual momentum strategy described in this paper, on the other hand, does succeed in vastly improving upon a total return momentum strategy, without using any information or instruments that would not have been available to investors in reality.

Our work also extends the research by Guitierrez and Pirinsky (2007), who document that momentum's long-term reversal in month 13 to 60 after portfolio formation can be attributed to the strategy's common-factor exposures. For a momentum strategy based on residual stock returns the authors observe that performance over the first year after formation is similar to that of total return momentum, but, contrary to total return momentum, long-run performance does not revert. This suggests that the difference between residual and total return momentum is negligible in year one and only becomes significant during subsequent years. However, we show that when risks are taken into account the momentum strategies' performances are in fact also dramatically different during the first 12 months after portfolio formation. As discussed above, we find that the risk-adjusted performance of residual momentum is double that of total return momentum; more consistent over the business cycle; less concentrated in the extremes of the cross-section; more robust to transaction costs and more consistent over time. Thus, the implications of residual momentum reach far beyond those pointed out by Guitierrez and Pirinsky (2007).

Overall, we conclude that residual momentum is a much stronger and much more robust effect than total return momentum. Our findings are consistent with the gradual-information-diffusion hypothesis that states that information diffuses only gradually across the investment public and that investor under-reaction is more strongly pronounced for firm-specific events than for common events [see, .e.g, Barberis, Schleifer and Vishny (1998), Daniel, Hirschleifer and Subrahmanyam (1998), Hong and Stein (1999), Hong, Lim and Stein (2000) and Gutierrez and Pirinsky (2007)] and present a serious challenge to the view that markets are efficient, even in the weakest form of the Efficient Markets Hypothesis.

Our findings also have important implications for the practical implementation of momentum trading strategies. Our results imply that investors, who are striving to achieve superior performance by engaging in momentum trading, have better prospects for success when using residual returns instead of total returns.

In what follows, Section 2 describes our data and construction of momentum portfolios. Sections 3 and 4 document the results of our empirical analyses and robustness tests, respectively. Finally Section 5 concludes.

2.2 Data and methodology

We use two subsamples of the CRSP universe of common stocks traded at the NYSE, Amex and NASDAQ exchanges over the period 1926 to 2007: (i) all stocks priced above \$1; and (ii) all large cap stocks (i.e., stocks with a market capitalization above \$1 billion by the end of 2007. This figure is inflated back by 5 percent per annum). Our data on common factors are from the webpage of Kenneth French (see footnote 15 in Chapter 1).

Our exploration into the returns of momentum strategies follows the common approach in the empirical literature [see, e.g., Jegadeesh and Titman (1993; 2001), Rouwenhorst (1998; 1999), Griffin, Ji and Martin (2003), Grundy and Martin (2003), Schwert (2003), and Gutierrez and Pirinsky (2007)]. The methodology involves two stages, where the first stage involves *ex ante* formation of portfolios based on past returns, and the second stage concerns *ex post* factor regressions of the resulting portfolio returns on common risk factors.

We start by allocating stocks to mutually exclusive decile portfolios based on 11-month one-month lagged total returns and residual returns. Residual returns are estimated using the Fama and French three-factor model:

$$r_{i,t} = \alpha_i + \beta_{1,i} RMRF_t + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + \varepsilon_{i,t} \tag{2.1}$$

where $r_{i,t}$ is the return on stock *i* in month *t* in excess of the risk-free rate, $RMRF_t$, SMB_t and HML_t are the excess returns on factor-mimicking portfolios for the market, size and value in month *t*, respectively, α_i, $\beta_{1,i}$, $\beta_{2,i}$ and $\beta_{3,i}$ are parameters to be estimated, and $\varepsilon_{i,t}$ is the residual return of stock *i* in month *t*. We estimate the regressions over 36-month rolling windows, i.e., over the period from *t*-36 until *t*-1, so that we have a sufficient number of return observations to obtain accurate estimates for stock exposures to the market, size and value. Only stocks which have a complete return history over the 36-month rolling regression window are included in our analysis.

With the momentum portfolios based on total return momentum, the top (bottom) decile contains the 10 percent of stocks with the highest (lowest) 11-month one-month lagged total returns. With the portfolios based on residual momentum, the top (bottom) decile contains the 10 percent of stocks with the highest (lowest) 11-month one-month lagged residual return standardized by its standard deviation over the same period. We argue that standardizing the residual return yields an improved measure since the residual can be a noisy estimate. Guitierrez and Pirinsky (2007) also standardize residual returns when they investigate the interaction between idiosyncratic stock return variation and long-run reversals. They argue that standardizing the residual return yields an improved measure of the extent to which a given firm-specific return shock is actually news, opposed to noise, thereby facilitating a better interpretation of the residual as firm-specific information. Note that we do not include the estimated alpha in the calculation of residual momentum because the alpha serves as a general control for misspecification in the model of expected stock returns. Moreover, over two-thirds of the observations behind the estimated alpha are outside the 11-month formation period which is relevant for residual momentum, as a result of which the alpha may, to a large extent, reflect extreme return observations in month *t*-36 to *t*-13.

Consistent with most of the literature, we assign equal weights to the stocks in each decile. We form the deciles using monthly, quarterly, semi-annually and yearly holding periods. With quarterly holding horizons, we rebalance the portfolios at the beginning of January, March, June and September; with semi-annually holding horizons, we rebalance at the beginning of January and June; and with yearly holding horizons, we rebalance only at the beginning of January.

Next, we consider the post-formation returns over the period January 1930 to December 2007 for the return differential between the top and bottom deciles. We look at the momentum strategies' returns, volatilities, Sharpe ratios and alphas relative to the Fama and French factors. To estimate alphas, we employ a conditional framework in the spirit of Grundy and Martin (2001) to account for the dynamic factor exposures of momentum strategies:

$$\begin{aligned} r_{i,t} = \alpha_i + \beta_{1,i} RMRF_t + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + \beta_{4,i} RMRF\_UP_t + \\ \beta_{2,i} SMB\_UP_t + \beta_{3,i} HML\_UP_t + \varepsilon_{i,t} \end{aligned} \tag{2.2}$$

where $RMRF\_UP_t$, SMB_UP_t and HML_UP_t are interaction variables that indicate the excess returns on factor-mimicking portfolios for the market, size and value in month t, respectively, when the premiums on the factors are positive over month t-12 to t-2, and are zero otherwise.

In later robustness checks (see Section 4), we show that residual momentum behaves consistently no matter if we use alternative specifications of common factors or different lengths for the rolling window we use to estimate the betas to the factor-mimicking portfolios for the market, size and value in Equation (2.1).

2.3 Residual momentum versus total return momentum

In this section we first discuss the rationale behind a residual momentum strategy. This is followed by an extensive comparison of the empirical characteristics of residual and total return momentum strategies.

2.3.1 Motivation

A conventional momentum strategy consists of buying past winner and selling past loser stocks ranked on their total return over the past period. We argue that such a strategy implicitly places a bet on persistence in common-factor returns, which will affect its risk and return characteristics. To illustrate this, consider the following example. If the market premium was positive during the formation period, a momentum strategy will typically be long in high-beta stocks and short in low-beta stocks, as high-beta stocks tend to outperform low-beta stocks during bullish environments. As a consequence, the net market beta of the momentum strategy will be positive. Similarly, when stocks with a high (low) book-to-market ratio performed relatively well during the formation period, the strategy will be tilted towards value (growth) stocks. The profitability of a momentum strategy will be positively affected by these dynamic exposures in case of persistence in factor returns, but negatively when factor returns revert.

Most authors document that a non-trivial portion of the risk of a traditional momentum strategy can be attributed to dynamic exposures to common factors, but empirical evidence does not unambiguously indicate that these exposures also contribute positively to profitability. For example, Moskowitz and Grinblatt (1999) and Nijman, Swinkels and Verbeek (2004) conclude that a large portion of the profitability of a momentum strategy is attributable to momentum in industry factors. Chordia and Shivakumar (2002) show that the profits to momentum strategies are explained by common macro-economic variables related to the business cycle. In addition, Chen and de Bondt (2004) report style momentum in equity returns and find that momentum strategies that buy stocks with characteristics (e.g., market cap and book-to-market ratio) of past winners and that sell stocks with characteristics of past losers perform well for periods up to one year and longer.

On the other hand, although Grundy and Martin (2001) find that a conditional version of the Fama and French model can explain up to 79 percent of the variance of momentum strategies, they report that momentum profits cannot be explained by time-varying exposures to the Fama and French factors and argue that the gains instead reflect momentum in the stock-specific components of returns. In fact, Grundy and Martin find that momentum strategies appear more profitable once their time-varying exposures to the Fama and French factors are taken into account.

In this section, we begin by decomposing the risks and profits of total return momentum into a component due to persistence in returns of the Fama and French factors and a component due to persistence in residual returns. We find that roughly 50 percent of the risks, but only 25 percent of the profits can be attributed to exposures to the Fama and French factors. Apparently, dynamic exposures to common factors contribute positively to the profitability of total return momentum. On the other hand, a disproportional large portion of the risks of total return momentum can be attributed to these dynamic exposures.

We also show that ranking stocks, not on their total returns, but on their residual (non-systematic returns) is a very effective approach to neutralize the dynamic factor exposures of a momentum strategy. We find that these exposures are roughly three to four times smaller than those of a total return momentum strategy. Thus, the empirical behaviour of residual momentum is consistent with the intuition behind the strategy. This lays the basis for the rest of this section, in which we extensively compare the risk and return characteristics of residual momentum strategies and conventional total return momentum strategies.

2.3.2 Main results

We start our empirical investigation by comparing and distinguishing between the performances of total return momentum and residual momentum. The main testable prediction which we explore is that total return momentum has significant exposures to common factors and therefore is more volatile than residual momentum. At the same time we investigate which portion of the profitability of total return momentum can be attributed to dynamic factor exposures and if there is any differential performance between total return momentum and residual momentum on a risk-adjusted basis.

To go to the heart of the issue, we examine if there is persistence in common factor returns. As we explained previously, persistence in common factor returns can potentially contribute positively to momentum's profitability. In Table 2.1 we look at persistence in market, size and value returns, by measuring the frequency with which the sign of the returns are the same during the formation period and the holding period.

Table 2.1

Persistence in common factor returns

This table shows the results of tests for persistence in the returns of the Fama and French market (RMRF), size (SMB), and value (HML) factors. We define a formation period and a holding period and calculate the probability that the sign of the returns over these periods is the same. We report results for 12-month formation periods excluding the most recent month and consider one-, three-, six-, and 12-month holding periods.

	Market (RMRF)	Size (SMB)	Value (HML)
1 month	57%	55%	57%
3 months	56%	54%	55%
6 months	59%	58%	58%
12 months	57%	61%	56%

Consistent with the definition of our momentum portfolios, we use 11-month formation periods and skip one month after formation. We use alternative holding periods of one month, one quarter, six months and one year. Under the null hypothesis of no persistence in factor returns, the frequencies in Table 2.1 should equal 50 percent. However, our empirical results indicate that the frequencies tend to be between 55 and 60 percent, which indicates that there is at least some amount of persistence in common factor returns.

Given the evidence of persistence in common factor returns we may expect the dynamic factor exposures of a total return momentum strategy to contribute positively to profitability. However, the question remains how large this contribution to performance is; how much risk is involved with these exposures; and what happens when we attempt to neutralize these dynamic exposures.We therefore continue by decomposing the risks and profits of total return momentum and residual momentum into a component due to persistence in common factor returns and a component due to persistence in residual returns using the conditional Fama and French model in Equation (2.2). The results in Panel A of Table 2.2 show that total return momentum exhibits strong dynamic exposures to the Fama and French factors. The exposures to the market, size and value factors are both economically and statistically significant. The results are independent of the length of the holding period. The adjusted R-squared values of the regressions indicate that up to 50 percent of the variance of total return momentum can be explained by dynamic factor exposures. These findings underline the importance of taking into account dynamic risk exposures when evaluating the risks and profits of momentum strategies.[2]

The results in Panel B of Table 2.2 indicate that residual momentum, on the other hand, exhibits much smaller factor exposures. More specifically, the conditional betas to the Fama and French factors of residual momentum are roughly three to four times smaller than those of total return momentum. For the one-month holding period, for example, the market beta after the market went down during the formation period is –0.35 for total return momentum, whereas it is –0.08 for residual momentum. The explanatory power of the regressions is also substantially lower for residual momentum with the regression R-squared ranging from 10 to 18 percent, compared to 32 to 49 percent for total return momentum. We can thus conclude that ranking stocks by their residual return turns out to be an effective approach to neutralize the dynamic factor exposures of classic momentum strategies.

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[2] When we evaluate the performance of total return momentum using the unconditional Fama-French model in Equation (2.1), the adjusted R-squared values of the regressions indicate that only 8 to 14 percent of the variance of the momentum strategy can be explained by factor exposures.

Table 2.2

Total return momentum versus residual momentum

This table shows the returns, volatilities, Sharpe ratios, alphas, betas to the market, size and value factors, and R-squared values for zero-investment momentum portfolios of stocks ranked by their 11-month one month lagged total return (Panel A) and residual return (Panel B) for one-, three-, six- and 12-month holding periods. An exact description of how the momentum portfolios are constructed can be found in Section 2. Alphas and betas are estimated using regression model (2) described in Section 2. All values are annualized. T-statistics are in parentheses.

Panel A. Total return momentum

	Return	Volatility	Sharpe	Alpha	RMRF	SMB	HML	RMRF_UP	SMB_UP	HML_UP	Adj. R-sq.
1 month	11.77	21.83	0.54	9.17	-0.35	-0.87	-1.11	0.73	1.08	1.10	49%
				(5.09)	(-8.05)	(-9.78)	(-19.31)	(12.22)	(10.34)	(12.86)	
3 months	9.64	21.48	0.45	7.35	-0.33	-0.87	-1.11	0.75	0.95	1.08	49%
				(4.16)	(-7.83)	(-9.97)	(-19.73)	(12.85)	(9.32)	(12.89)	
6 months	7.97	21.01	0.38	5.95	-0.33	-0.79	-1.01	0.70	0.94	0.89	44%
				(3.27)	(-7.50)	(-8.80)	(-17.28)	(11.71)	(8.92)	(10.32)	
12 months	4.07	17.67	0.23	1.51	-0.20	-0.61	-0.62	0.54	0.93	0.43	32%
				(0.90)	(-4.82)	(-7.34)	(-11.48)	(9.76)	(9.63)	(5.45)	

Table 2.2 (continued)

Panel B. Residual momentum

	Return	Volatility	Sharpe	Alpha	RMRF	SMB	HML	RMRF_UP	SMB_UP	HML_UP	Adj. R-sq.
1 month	12.73	12.50	1.02	11.97	-0.08	-0.18	-0.32	0.19	0.33	0.23	11%
				(8.83)	(-2.42)	(-2.75)	(-7.36)	(4.20)	(4.17)	(3.56)	
3 months	11.05	12.46	0.89	10.83	-0.13	-0.15	-0.42	0.28	0.14	0.31	18%
				(8.35)	(-3.99)	(-2.36)	(-10.23)	(6.52)	(1.88)	(4.95)	
6 months	9.04	12.49	0.72	9.96	-0.10	-0.12	-0.45	0.17	0.02	0.26	18%
				(7.64)	(-3.13)	(-1.82)	(-10.75)	(3.97)	(0.22)	(4.15)	
12 months	5.40	10.71	0.50	6.10	0.03	-0.11	-0.33	-0.01	0.11	0.12	10%
				(5.22)	(1.23)	(-1.89)	(-8.78)	(-0.28)	(1.56)	(2.20)	

To further investigate the impact of neutralizing momentum's dynamic factor exposures on portfolio risk, we evaluate the volatilities of total return momentum and residual momentum. We find that the volatility of residual momentum is only about half that of total return momentum. For example, using a one-month holding period, total return momentum has an annualized volatility of 21.83 percent, versus only 12.50 percent for residual momentum. Hence, ranking stocks by their residual return substantially reduces the risk of a momentum strategy.

We now turn to investigating the impact of neutralizing momentum's dynamic factor exposures on portfolio profitability. As expected, we can conclude that the dynamic style exposures of total return momentum are contributing positively to profitability, as the alphas of the total return momentum strategies are roughly 25 percent lower than their raw returns. For example, using a one-month holding period, the return of total return momentum is 11.77 percent per annum, while the alpha in this case is only 9.17 percent. Importantly, the portion of the risk of total return momentum that can be attributed to these exposures is substantially larger (i.e., the adjusted R-squared values from the regressions indicate that this portion is about 50 percent). Therefore one might expect residual momentum to have a lower return, but a higher Sharpe ratio than total return momentum.

One of our key findings, however, is that ranking stocks on their residual return does not come at the expense of profitability of the strategy. Both the return and the alpha of residual momentum are in fact higher than those of total return momentum. For example, for a one-month holding period, Table 2.2 shows that the return of residual momentum is about one percent higher than for total return momentum, while the alpha is even 2.8 percent higher. In order to understand this result, we first note that, compared to total return momentum, residual momentum has less weight in stocks with large exposures to common factors, but more weight in stocks with high residual returns. Our results imply that the loss in profitability which results from the first effect is more than compensated for by a gain in profitability which is associated with the second effect. Hence, despite our finding that factor returns tend to persist to a certain degree, the dynamic factor exposures of total return momentum strategies are not only suboptimal from a risk point of view, but also from a return perspective.

Because a residual momentum strategy yields similar profits as a total return momentum strategy, but with a volatility that is roughly 40 percent lower, the Sharpe ratio of residual momentum is approximately double that of total return momentum. This implies that momentum, which is already one of the biggest anomalies in empirical finance, is twice as large an anomaly if stocks are ranked on their residual return instead of their total return.[3] Our empirical results are consistent with the body of literature that attempts to explain the momentum anomaly by behavioural biases of investors [see, e.g., Barberis, Schleifer and Vishny (1998), Daniel, Hirschleifer and Subrahmanyam (1998), and Hong and Stein (1999)]. In particular, our finding that the largest portion of the profits of total return momentum can be attributed to exposures to idiosyncratic factors is supportive of the gradual-formation-diffusion hypothesis of Hong and Stein (1999) that predicts that firm-specific information diffuses only gradually across the investment public.

Another important implication of our findings is that residual momentum is a substantially longer-lived phenomenon than total return momentum. While the alpha of total return momentum dwindles to an economically and statistically insignificant figure of 1.5 percent using a 12-month holding period, residual momentum still generates significant risk-adjusted returns of over six percent per annum at this horizon. This finding is inconsistent with the view that momentum profits can not be captured because of the high turnover which is required by the strategy. The economically large risk-adjusted returns which we document for residual momentum at yearly rebalancing frequencies pose a serious challenge to the Efficient Market Hypothesis – even in its weakest form. These results are in line with the recent findings of Gutierrez and Pirinsky (2007), who focus on the long-term performance of residual versus total return momentum strategies. They find that, whereas total return momentum profits revert (i.e., turn negative) at horizons beyond one year, residual momentum continues to generate positive returns.[4]

2.3.3 Business cycle effects

Having established that the long-term Sharpe ratio of residual momentum is approximately double that of total return momentum, we continue our analysis with investigating the performance of total return momentum and residual momentum over the business cycle. Chordia and Shivakumar (2002) report that total return momentum performs poorly during contractions as defined by the NBER. One natural question to ask is if residual momentum exhibits similar performances over the business cycle as total return momentum. To

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[3] Following the work of Jegadeesh and Titman (1993), momentum has been investigated by other authors in the United States before 1960s; in areas outside the United States; and subsequent to the period after the publication of their results [see, e.g., Rouwenhorst (1998, 1999), Jegadeesh and Titman (2001), Griffin, Ji and Martin (2003), and Schwert (2003)].

[4] Interestingly, Gutierrez and Pirinsky (2007) also show returns of residual versus total return momentum strategies over the first 12 months after portfolio formation, but discuss these results only briefly, noting that the differences in return are small. This is consistent with our results in Table 2. However, our results also show that when risk is taken into consideration next to return, residual momentum is, in fact, far superior to total return momentum.

investigate this issue, we split the momentum returns according to being in phase 1 or 2 of an NBER expansion (equally splitting the total expansionary period in two halves) or in phase 3 or 4 of an NBER recession.

Table 2.3

Return versus residual momentum over the NBER business cycle

This table shows the returns on zero-investment momentum portfolios of stocks ranked by their 11-month one month lagged total return and residual return over the NBER business cycle for one-month holding periods. An exact description of how the momentum portfolios are constructed can be found in Section 2. For comparison, the table also shows the returns on the market, size and value factors and risk-free rate over the NBER business cycle. T-statistics are in parentheses.

	RMRF	SMB	HML	RF	Total return momentum	Residual momentum
Expansion 1	12.18	5.10	5.57	3.11	12.12	13.40
	(3.72)	(2.56)	(2.45)	(19.82)	(3.13)	(6.02)
Expansion 2	7.91	2.90	4.48	4.13	18.15	14.10
	(2.33)	(1.41)	(1.91)	(25.46)	(4.53)	(6.12)
Contraction 3	-23.15	-7.20	3.16	4.48	3.88	9.38
	(-3.25)	(-1.66)	(0.64)	(13.16)	(0.46)	(1.94)
Contraction 4	16.10	10.68	0.43	3.31	-9.17	9.57
	(2.26)	(2.47)	(0.09)	(9.73)	(-1.09)	(1.98)

The results in Table 2.3 indicate that total return momentum has a high average performance during expansionary periods, at 12.12 percent per annum in phase 1 and 18.15 percent in phase 2. In contrast, the performance is only 3.88 percent in the first phase of recessionary periods and a very negative –9.17 percent in the second stage of recessions. One reason for this is that in phase 4 of the business cycle factor returns tend to revert, which hurts the total momentum strategy, as explained before. For example, market returns turn from negative in the first part of recessions to positive in the second part, see column 1 in Table 2.3. Because momentum looks back 12 months it will tend to have a negative beta (long stocks with a low beta and short stocks with a high beta), which results in losses when a market rally follows.

In the final column of Table 2.3 we see that the performance of residual momentum is quite stable over the business cycle. During recessions it still averages returns above nine percent per annum. By design residual momentum has much less dynamic exposures to the factor returns and hence it is not susceptible to losses when factor returns revert. Overall, our results indicate that residual momentum produces consistent outperformance in all economic environments.

2.3.4 Small cap stock exposures

The next issue we investigate is if total return momentum and residual momentum are concentrated in different segments of the equity market. Jegadeesh and Titman (1993) show that the top and bottom deciles of stocks ranked on total return on average contain high beta and small cap stocks. In this subsection we illustrate the corresponding characteristics of residual momentum. In particular, in Table 2.4 we show for each decile portfolio and for the D10-D1 hedge portfolio the average pre- and post-ranking return and volatility, as well as the ex-post exposures to the market, size and value factors.

We observe that, as expected, total return momentum has a higher dispersion in pre-ranking returns and volatility. We also confirm the findings of Jegadeesh and Titman in that the decile 1 and 10 portfolios have a higher market beta and a lower market cap than the other deciles. Moreover, it appears that the extreme portfolios exhibit increased levels of firm-specific risk. Campbell and Taksler (2003) show that these characteristics are negatively related to bond yields. As such, our findings are consistent with the notion of Agarwal and Taffler (2008), and Avramov, Chordia, Gergana, and Philipov (2007) that momentum trading strategies are concentrated in the highest credit-risk firms that are more likely to suffer financial distress.

Interestingly, the corresponding characteristics of decile portfolios of stocks sorted on their residual momentum appear to be quite different. We first note that ex-post the average returns of the residual momentum deciles increase more monotonously than those of total return momentum, also resulting in the slightly higher spread of 12.73 percent between decile 10 and 1, compared to 11.77 percent of total return momentum. Furthermore, residual momentum only has minor differences in market betas and size exposures across all deciles. Hence, residual momentum does not appear to be tilted towards a specific market segment of the equity market such as small cap stocks with elevated levels of firm-specific risk.

Table 2.4

Decile portfolios of stock sorted on total returns and residual returns

This table shows the pre- and post-ranking returns, volatilities, Sharpe ratios, betas to the market, size and value factors, and R-squared values for decile portfolios of stocks ranked by their 11-month one month lagged total return (Panel A) and residual return (Panel B) for one-month holding periods. An exact description of how the momentum portfolios are constructed can be found in Section 2. Alphas and betas are estimated using regression model (1) described in Section 2. All values are annualized.

Panel A. Total return momentum

	Pre-ranking		Post-ranking						
	Return	Volatility	Return	Volatility	Sharpe	RMRF	SMB	HML	Adj. R-sq.
D1 (losers)	-46.30	38.29	11.49	32.73	0.35	1.15	1.00	0.53	0.83
D2	-19.87	32.92	10.14	27.13	0.37	1.07	0.67	0.46	0.89
D3	-8.59	30.95	9.76	24.93	0.39	1.03	0.48	0.44	0.90
D4	-0.19	30.13	10.55	23.36	0.45	0.97	0.55	0.34	0.92
D5	7.16	30.22	12.20	22.71	0.54	0.95	0.53	0.33	0.93
D6	14.45	31.11	12.52	21.49	0.58	0.93	0.47	0.22	0.92
D7	22.37	32.78	14.03	22.28	0.63	0.97	0.50	0.18	0.92
D8	32.11	35.64	15.19	22.48	0.68	0.96	0.60	0.14	0.92
D9	46.46	41.10	18.32	23.97	0.76	0.96	0.77	-0.01	0.87
D10 (winners)	88.51	60.46	23.26	29.50	0.79	1.12	1.07	-0.09	0.85
D10-D1	-	-	11.77	21.82	0.54	-0.03	0.07	-0.62	0.13

Table 2.4 (continued)

Panel B. Residual momentum

	Pre-ranking		Post-ranking						
	Return	Volatility	Return	Volatility	Sharpe	RMRF	SMB	HML	Adj. R-sq.
D1 (losers)	-23.04	30.15	7.12	25.15	0.28	1.04	0.60	0.33	0.91
D2	-10.93	31.74	11.16	25.31	0.44	1.03	0.68	0.33	0.91
D3	-3.43	33.08	10.36	23.46	0.44	0.99	0.57	0.29	0.93
D4	3.09	33.89	12.13	24.69	0.49	1.04	0.55	0.34	0.93
D5	9.12	34.81	13.96	24.64	0.57	1.00	0.67	0.35	0.94
D6	15.59	36.31	14.11	24.15	0.58	0.99	0.67	0.30	0.94
D7	22.48	37.80	15.08	24.59	0.61	1.02	0.63	0.30	0.93
D8	30.30	38.91	16.79	23.98	0.70	1.01	0.60	0.25	0.92
D9	40.33	39.95	17.72	24.07	0.74	0.98	0.69	0.20	0.91
D10 (winners)	52.25	36.88	19.85	25.04	0.79	1.05	0.69	0.12	0.90
D10-D1	-	-	12.73	12.49	1.02	0.01	0.09	-0.21	0.05

2.3.5 Excluding small cap stocks

Continuing our empirical investigation we address the concern that most of the performance differential between total return and residual momentum might be concentrated in small cap stocks. To this end, we investigate if the performance differential can also be observed when the universe of stocks is restricted to liquid large caps. In this subsection we therefore look at the performance of residual momentum when applied exclusively to large cap stocks. In particular, we require that the market capitalization of a stock is at least one billion by the end of 2007. This threshold level is deflated by five percent per annum going back in time. On average, roughly 30 percent of the stocks in the CRSP universe are below this cut-off over our sample period. The results are shown in Table 2.5.

As expected, the average performance of residual momentum is lower for the large cap universe. For example, for a three-month holding period the average annualized return is now 6.59 percent, compared to 11.05 percent when using the full sample of stocks, see Table 2.2. However, with a Sharpe ratio of 0.45 a strong residual momentum effect remains. And, similar to our earlier findings, this is almost twice as high as the corresponding figure for the total return momentum strategy, which has a Sharpe of only 0.24 for a three-month holding period. For the large cap universe the difference in Sharpe ratios is also primarily driven by the lower volatility of the residual momentum strategy. Hence our main conclusions hold up when we restrict our sample to a universe of large cap stocks.

2.3.6 Calendar month effects

Next, we investigate the performances of total return momentum and residual momentum per calendar month. Several authors document strong seasonal patterns in momentum returns. For example, Jegadeesh and Titman (1993; 2001) and Grinblatt and Moskowitz (2004) find a January effect for the total return momentum strategy. In particular, average returns in January are found to be negative. The cited reason is the tax-loss selling effect. Fund managers sell small-cap loser stocks in December and the resulting downwards price pressure in December is followed by a correction in January. This causes a large positive return for a total return momentum strategy in December followed by a large negative return in January. We refer to Roll (1983), Griffiths and White (1993), and Ferris, D'Mello, and Hwang (2001) for a detailed documentation of this effect.

Table 2.5

Return versus residual momentum for large cap stocks

This table shows the returns, volatilities, Sharpe ratios, alphas, betas to the market, size and value factors, and R-squared values for zero-investment momentum portfolios of stocks ranked by their 11-month one month lagged total return (Panel A) and residual return (Panel B) for one-, three-, six- and 12-month holding periods. The analysis is performed using exclusively large cap stocks (i.e., stocks with a market capitalization above $1 billion by the end of 2007. This figure is inflated back by 5 percent per annum.). An exact description of how the momentum portfolios are constructed can be found in Section 2. Alphas and betas are estimated using regressions model (2) described in Section 2. All values are annualized. T-statistics are in parentheses.

Panel A. Total return momentum

	Return	Volatility	Sharpe	Alpha	RMRF	SMB	HML	RMRF_UP	SMB_UP	HML_UP	Adj. R-sq.
1 month	8.18	23.31	0.35	7.40	-0.57	-0.38	-1.11	0.87	0.59	0.86	46%
				(3.76)	(-12.04)	(-3.92)	(-17.68)	(13.48)	(5.17)	(9.24)	
3 months	5.42	22.53	0.24	4.41	-0.50	-0.33	-1.10	0.84	0.45	0.89	45%
				(2.29)	(-10.65)	(-3.42)	(-17.78)	(13.30)	(4.07)	(9.75)	
6 months	5.10	21.62	0.24	5.00	-0.44	-0.33	-1.03	0.73	0.42	0.69	41%
				(2.61)	(-9.40)	(-3.50)	(-16.74)	(11.50)	(3.82)	(7.51)	
12 months	2.98	18.02	0.17	2.73	-0.21	-0.24	-0.74	0.42	0.48	0.34	29%
				(1.56)	(-5.02)	(-2.81)	(-13.25)	(7.27)	(4.71)	(4.09)	

Table 2.5 (continued)

Panel B. Residual momentum

	Return	Volatility	Sharpe	Alpha	RMRF	SMB	HML	RMRF_UP	SMB_UP	HML_UP	Adj. R-sq.
1 month	7.72	14.92	0.52	8.77	-0.29	-0.07	-0.27	0.37	-0.08	0.13	14%
				(5.51)	(-7.59)	(-0.89)	(-5.31)	(6.98)	(-0.85)	(1.72)	
3 months	6.59	14.81	0.45	7.51	-0.26	-0.07	-0.31	0.39	-0.13	0.18	15%
				(4.78)	(-6.96)	(-0.91)	(-6.18)	(7.51)	(-1.47)	(2.36)	
6 months	5.66	14.77	0.38	7.13	-0.22	-0.22	-0.33	0.31	-0.07	0.18	17%
				(4.59)	(-5.99)	(-2.81)	(-6.58)	(6.00)	(-0.82)	(2.46)	
12 months	3.33	13.72	0.24	4.68	0.00	-0.28	-0.20	0.06	0.03	-0.01	8%
				(3.08)	(0.03)	(-3.72)	(-4.06)	(1.15)	(0.29)	(-0.15)	

Table 2.6

Return versus residual momentum per calendar month

This table shows the return per calendar month on zero-investment momentum portfolios of stocks ranked by their 11-month one month lagged total return (Panel A) and residual return (Panel B) for one-, three-, six- and 12-month holding periods. An exact description of how the momentum portfolios are constructed can be found in Section 2. T-statistics are in parentheses.

Panel A. Total return momentum

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1 month	-2.75	1.74	1.71	1.90	1.49	1.36	-0.48	0.05	1.03	0.82	1.18	3.71
	(-3.94)	(2.49)	(2.45)	(2.72)	(2.14)	(1.95)	(-0.68)	(0.08)	(1.47)	(1.18)	(1.69)	(5.33)
3 months	-2.75	1.67	1.06	1.90	1.17	1.12	-0.48	0.06	0.26	0.82	1.82	3.00
	(-3.99)	(2.43)	(1.53)	(2.76)	(1.69)	(1.62)	(-0.69)	(0.08)	(0.38)	(1.19)	(2.64)	(4.36)
6 months	-2.75	1.67	1.06	1.51	1.23	1.03	-0.48	0.06	0.26	0.61	1.40	2.37
	(-4.06)	(2.47)	(1.56)	(2.23)	(1.82)	(1.52)	(-0.70)	(0.09)	(0.39)	(0.90)	(2.07)	(3.50)
12 months	-2.75	1.67	1.06	1.51	1.23	1.03	-0.87	-0.36	0.18	-0.12	0.78	0.72
	(-4.86)	(2.96)	(1.87)	(2.67)	(2.17)	(1.82)	(-1.55)	(-0.64)	(0.31)	(-0.21)	(1.39)	(1.27)

Table 2.6 (continued)

Panel B. Residual momentum

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1 month	-0.24	1.14	1.32	1.66	1.43	1.51	0.83	0.51	1.16	0.86	0.66	1.90
	(-0.59)	(2.80)	(3.26)	(4.10)	(3.51)	(3.71)	(2.03)	(1.25)	(2.86)	(2.11)	(1.63)	(4.68)
3 months	-0.24	1.30	1.02	1.66	0.81	1.21	0.83	0.36	0.79	0.86	1.00	1.45
	(-0.59)	(3.20)	(2.50)	(4.10)	(1.98)	(2.99)	(2.03)	(0.88)	(1.94)	(2.11)	(2.47)	(3.58)
6 months	-0.24	1.30	1.02	1.08	0.44	1.16	0.83	0.36	0.79	0.73	0.38	1.21
	(-0.59)	(3.19)	(2.49)	(2.64)	(1.07)	(2.85)	(2.03)	(0.88)	(1.93)	(1.78)	(0.94)	(2.96)
12 months	-0.24	1.30	1.02	1.08	0.44	1.16	-0.11	0.10	-0.07	0.35	0.29	0.09
	(-0.69)	(3.75)	(2.93)	(3.10)	(1.26)	(3.35)	(-0.32)	(0.28)	(-0.21)	(1.01)	(0.84)	(0.27)

Because residual momentum is ex ante neutral with respect to market cap segments, calendar effects might affect the strategy differently. To investigate this issue, we compute the average monthly returns during each calendar month for the total return momentum versus the residual momentum strategy. The results in Panel A of Table 2.6 confirm the strong negative performance of total return momentum in Januaries, with an average return of –2.75 percent. Strikingly, residual momentum hardly suffers in Januaries, with an average (non-significant) return of -0.24 percent, as shown in Panel B.

Our results illustrate another notable seasonality in momentum returns. We observe that most of the profits of total return momentum strategies are generated in the first half of the calendar year. Total return momentum profits are significantly positive over the months February until June, while in the second half of the calendar year total return momentum only generates a significant excess return over the month December. By contrast, we do not observe any obvious calendar effects in the returns of residual momentum. We thus conclude that, unlike total return momentum, residual momentum is not systematically plagued by seasonal patterns.

2.3.7 Performance over time

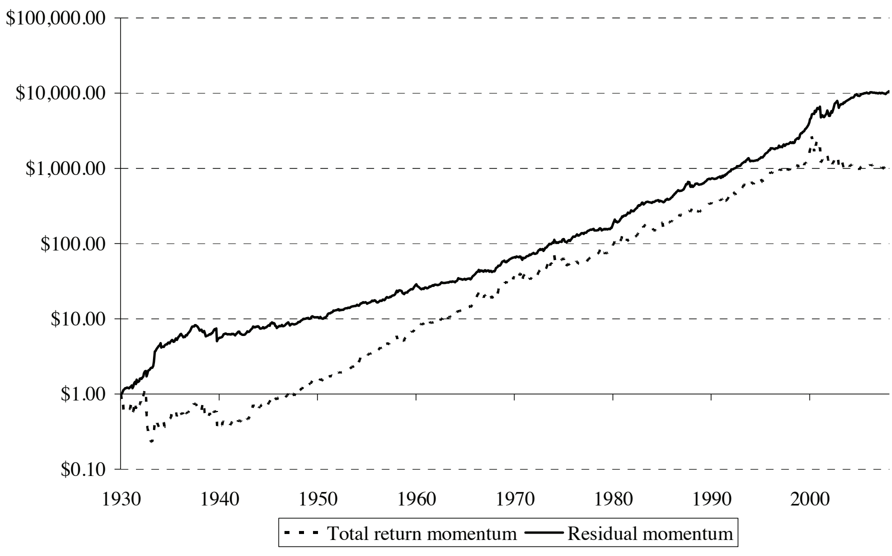
Proceeding further, we investigate the extent to which the performance differential between the two momentum strategies varies over time. Are there, for example, specific time periods in which reversals in factor returns hurt the performance of total return momentum? Or does residual momentum consistently earn higher risk-adjusted returns than total return momentum? To investigate this issue, we examine the cumulative performances and drawdowns of total return momentum and residual momentum in Figure 2.1 and 2.2, respectively. The drawdown at any given moment is calculated by comparing the cumulative return at that point in time to the all-time high cumulative return which was achieved up to that point in time. Thus, the drawdown is by definition zero percent at best, in case the strategy is at an all-time high, and negative otherwise.

Figures 2.1 and 2.2 show that residual momentum generates much more consistent returns than total return momentum. For example, total return momentum suffers from a maximum drawdown magnitude of 80 percent negative and a maximum drawdown length of more than 15 years during the early years of our sample period. Residual momentum also suffers its worst drawdown during this period, but with a magnitude and length less than half as severe as for total return momentum. The second worst drawdown for total return momentum and residual momentum occurs during the most recent decade and paints a very similar story. During the post-2000 period total return momentum suffers a drawdown exceeding 60 percent, from which it still has not recovered towards the end of the sample period, while residual momentum suffers a drawdown of less than 30 percent, from which it has already fully recovered. Thus, residual momentum is not only less volatile than total return momentum in the short run, but also exhibits less downside risk over longer periods of time.

Figure 2.1

Return versus residual momentum over time

This figure shows the cumulative return on zero-investment momentum portfolios of stocks ranked by their 11-month one month lagged total return and residual return for one-month holding periods. An exact description of how the momentum portfolios are constructed can be found in Section 2.

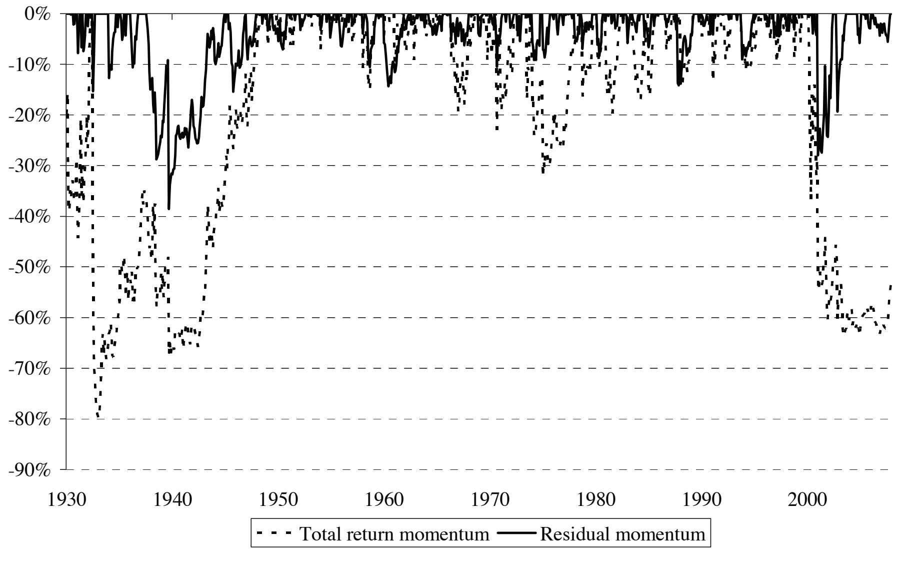


Perhaps an even more notable observation is that total return momentum profits have been both statistically and economically insignificant subsequent to the period after the publication of a large number of academic studies on the momentum anomaly (around the end of the 1990s). This observation suggests that the public dissemination of the momentum anomaly may have affected its profitability. We conjecture that it could well be the case that increased investment activities by professional investors such as hedge funds has arbitraged away a large portion of the anomalous profits of conventional total return momentum strategies. Interestingly, contrary to total return momentum, the performance of residual momentum does not appear to have weakened over the most recent time period.

Figure 2.2

Drawdown of return versus residual momentum

This figure shows the drawdown for zero-investment momentum portfolios of stocks ranked by their 11-month one month lagged total return and residual return for one-month holding periods. An exact description of how the momentum portfolios are constructed can be found in Section 2.



To more precisely evaluate the performances of both momentum strategies over time, we list the performances of total return momentum and residual momentum per decade in Table 2.7. For comparison, the table also shows the returns per decade on the market, size and value factors and the risk-free rate. The results in Table 2.7 show that no premium for total return momentum can be observed during two decades, namely the 1930s and the post-2000 period. Moreover, the premium during the 1970s is only marginally significant from a statistical point of view. Residual momentum, on the other hand, delivers annualized returns of at least six percent per annum during each decade in our sample, and, except for the 1940s, the residual momentum premium is statistically significant for all decades in our sample. Compared to the returns on the other factors in the Fama and French three-factor model, both momentum strategies have economically large and statistically significant premiums. For example, the premium on the market factor is only statistically significant during two out of eight decades; and the premium on the size factor and value factors is only statistically significant during one decade. Overall, the results in this subsection indicate that residual momentum is robust over time and a much more consistent phenomenon than total return momentum.

Table 2.7

Return versus residual momentum per decade

This table shows the returns on zero-investment momentum portfolios of stocks ranked by their 11-month one month lagged total return and residual return per decade for one-month holding periods. An exact description of how the momentum portfolios are constructed can be found in Section 2. For comparison, the table also shows the returns per decade on the market, size and value factors. T-statistics are in parentheses.

	RMRF	SMB	HML	RF	Total return momentum	Residual momentum
1930s	5.49	10.66	0.41	0.55	-0.53	19.88
	(0.93)	(3.00)	(0.10)	(3.82)	(-0.08)	(5.04)
1940s	10.07	4.31	9.56	0.41	14.67	6.61
	(1.71)	(1.21)	(2.37)	(2.84)	(2.13)	(1.67)
1950s	15.64	-0.52	3.36	1.86	16.95	10.40
	(2.66)	(-0.15)	(0.83)	(12.91)	(2.46)	(2.63)
1960s	5.04	4.68	3.23	3.81	17.69	8.63
	(0.86)	(1.32)	(0.80)	(26.48)	(2.56)	(2.19)
1970s	1.51	3.42	7.83	6.14	11.16	10.81
	(0.26)	(0.96)	(1.94)	(42.65)	(1.62)	(2.74)
1980s	8.80	0.17	5.44	8.55	13.84	14.43
	(1.50)	(0.05)	(1.35)	(59.44)	(2.01)	(3.66)
1990s	12.80	-0.67	-3.58	4.82	17.72	18.69
	(2.18)	(-0.19)	(-0.89)	(33.50)	(2.57)	(4.74)
2000-present	0.03	6.19	8.12	3.20	0.35	12.26
	(0.01)	(1.56)	(1.80)	(19.86)	(0.05)	(2.78)

2.4 Robustness checks and follow-up empirical tests

In this section we perform a range of tests to examine the robustness of our results to various choices we made with respect to the design of our research.

2.4.1 Excluding stocks with short return histories

To be able to estimate the Fama and French three-factor model in Equation (2.1) we require stocks to have a complete return history over the 36-month rolling regression window. Consequently, a large number of stocks from the CRSP universe is excluded at each point in time. For example, when we require stocks to have a complete return history over 11-month rolling windows the average number of stocks in our cross-section is 1,306, but this number drops to 1,112 when we extend the window to 36 months.[5] To alleviate concerns that the performance differential between total return momentum and residual momentum strategies can be attributed (perhaps partly) to excluding these stocks from the analysis, we additionally investigate the performance of a total return momentum strategy that also requires stocks to have a complete return history over the 36-month rolling regression window to be included in the portfolio.

Table 2.8 shows the results of this momentum strategy. Comparing these results with those in Table 2.2 (Panel A) we observe that the average returns for the one-month and three-month holding periods are very similar, whereas the average returns for the six-month and 12-month holding periods are somewhat better when using the full sample of stocks. Volatility, Sharpe and the factor exposures are also similar. Hence we conclude that the return momentum results are hardly affected by only investing in stocks with a complete 36-month return history at each point in time. We can therefore safely say that the superior performance of residual momentum is not related to the fact we require stocks to exist for at least three years.

2.4.2 60-month rolling windows

We also investigate if our results are sensitive to the length of the rolling window we use to estimate the betas to the factor-mimicking portfolios for the market, size and value in

[5] Please note that the number of stocks in the cross-section of our sample is substantially smaller than the number of stocks (2,818) on which the WML of French (2008) is based. This difference can be attributed to the fact that we exclude penny stocks from our analysis.

Table 2.8

Total return momentum excluding young stocks

This table shows the returns, volatilities, Sharpe ratios, alphas, betas to the market, size and value factors, and R-squared values for zero-investment momentum portfolios of stocks ranked by their 11-month one month lagged total return for one-, three-, size- and 12-month holding periods. The main difference with the analysis reported in Table 2.2 is that stocks with less than 36 historical return observations over the past three years are excluded from the analysis. An exact description of how the momentum portfolios are constructed can be found in Section 2; and an exact description of which stocks are excluded from the analysis can be found in Section 4.1.

	Return	Volatility	Sharpe	Alpha	RMRF	SMB	HML	RMRF_UP	SMB_UP	HML_UP	Adj. R-sq.
1 month	11.78	21.29	0.55	9.33	-0.34	-0.81	-1.07	0.72	0.98	1.06	47%
				(5.24)	(-8.02)	(-9.26)	(-18.78)	(12.35)	(9.52)	(12.49)	
3 months	9.87	21.28	0.46	7.97	-0.33	-0.82	-1.10	0.74	0.82	1.05	48%
				(4.50)	(-7.75)	(-9.37)	(-19.32)	(12.67)	(8.03)	(12.50)	
6 months	9.35	20.88	0.45	7.26	-0.34	-0.75	-0.97	0.73	0.87	0.89	43%
				(3.99)	(-7.72)	(-8.33)	(-16.73)	(12.13)	(8.27)	(10.26)	
12 months	5.53	17.69	0.31	3.10	-0.21	-0.57	-0.63	0.55	0.86	0.48	32%
				(1.84)	(-5.13)	(-6.92)	(-11.77)	(9.89)	(8.82)	(6.05)	

Table 2.9

Residual momentum using 60-month rolling windows

This table shows the returns, volatilities, Sharpe ratios, alphas, betas to the market, size and value factors, and R-squared values for zero-investment momentum portfolios of stocks ranked by their 11-month one month lagged residual return for one-, three-, size- and 12-month holding periods. The main difference with the analysis reported in Table 2.2 is that residual returns are estimated relative to the Fama and French factor model using 60-month (instead of 36-month) rolling windows. An exact description of how the momentum portfolios are constructed can be found in Section 2.

	Return	Volatility	Sharpe	Alpha	RMRF	SMB	HML	RMRF_UP	SMB_UP	HML_UP	Adj. R-sq.
1 month	11.79	12.18	0.97	12.44	-0.21	-0.17	-0.39	0.37	0.10	0.21	21%
				(9.82)	(-6.34)	(-2.60)	(-9.53)	(8.50)	(1.41)	(3.46)	
3 months	10.47	12.61	0.83	11.42	-0.16	-0.15	-0.48	0.34	0.01	0.27	24%
				(8.90)	(-4.90)	(-2.36)	(-11.74)	(7.85)	(0.15)	(4.37)	
6 months	9.38	12.06	0.78	10.67	-0.13	-0.11	-0.50	0.25	-0.02	0.27	24%
				(8.67)	(-3.98)	(-1.81)	(-12.57)	(5.89)	(-0.25)	(4.64)	
12 months	5.34	11.05	0.48	6.28	-0.03	-0.09	-0.39	0.11	0.06	0.15	15%
				(5.29)	(-1.05)	(-1.51)	(-10.37)	(2.65)	(0.91)	(2.74)	

Table 2.10

Residual momentum incorporating industry effects

This table shows the returns, volatilities, Sharpe ratios, alphas, betas to the market, size and value factors, and R-squared values for zero-investment momentum portfolios of stocks ranked by their 11-month one month lagged residual return for one-, three-, size- and 12-month holding periods. The main difference with the analysis reported in Table 2.2 is that residual returns are estimated relative to a factor model that augments the three Fama and French factors with industry factors. An exact description of how the momentum portfolios are constructed can be found in Section 2; and an exact description of how the industry factors are constructed can be found in Section 4.3. Alphas and betas are estimated using regressions model (2) described in Section 2. All values are annualized. T-statistics are in parentheses.

	Return	Volatility	Sharpe	Alpha	RMRF	SMB	HML	RMRF_UP	SMB_UP	HML_UP	Adj. R-sq.
1 month	11.79	12.38	0.95	10.66	0.00	-0.17	-0.29	0.08	0.37	0.27	9%
				(7.83)	(0.01)	(-2.46)	(-6.74)	(1.76)	(4.67)	(4.20)	
3 months	10.18	11.94	0.85	9.57	0.02	-0.19	-0.45	0.08	0.24	0.42	14%
				(7.51)	(0.64)	(-3.03)	(-11.00)	(1.89)	(3.25)	(6.97)	
6 months	8.66	11.21	0.77	9.37	0.01	-0.09	-0.46	0.05	-0.04	0.35	17%
				(7.95)	(0.23)	(-1.56)	(-12.14)	(1.31)	(-0.53)	(6.26)	
12 months	6.09	9.91	0.61	6.69	0.00	0.02	-0.38	0.05	-0.03	0.21	15%
				(6.35)	(-0.07)	(0.33)	(-11.17)	(1.31)	(-0.55)	(4.23)	

Equation (2.1). To this end we consider the effect of using 60-month instead of 36-month rolling windows. All other settings are exactly the same as in our main analysis described in Section 2. The results, which can be found in Table 2.9, are very similar to those presented in Table 2.2. We also repeated the analysis using 24-month rolling windows. The results are again very similar to those presented in Table 2.2. For the sake of brevity, these results are not reported in tabular form and available upon request.

2.4.3 Industry effects

The next issue we investigate is related to findings from several authors that the Fama and French factors do not fully suffice to describe the returns on industry portfolios [see, e.g., Fama and French (1997)]. While sorting stocks on their residual return relative to the Fama and French factors ensures that the momentum strategy is neutral to size and value effects, the strategy is not necessarily neutral to industries. In this subsection we investigate what portion of the risk of total return momentum can be attributed to industries and is not captured by the Fama and French factors.

Following Pastor and Stambaugh (2002a; 2002b), we employ a Principal Components Analysis (PCA) to construct statistical factors that capture industry-specific effects on a rolling basis. At each point in time, we develop time-series of residual excess returns for industries by regressing the excess returns on the 30 industry portfolios of French (2008), a constant and the three factors described in Equation (2.1). Again we use a 36-month rolling regression window. Next, we conduct a PCA on the time-series of the residuals of each regression plus the intercept from that regression. We take the first five normalized eigenvectors as portfolios weights for the industries' residual returns and add the resulting principal component factors to the three-factor model, which results in the following eight-factor model:

$$
\begin{aligned}
(2.3) \qquad & r_{i,t} = \alpha_i + \beta_{1,i} RMRF_t + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + \beta_{4,i} PC1_t + \beta_{5,i} PC2_t + \\
& \beta_{6,i} PC3_t + \beta_{7,i} PC4_t + \beta_{8,i} PC5_t + \varepsilon_{i,t}
\end{aligned}
$$

where $PC1_t$, $PC2_t$, $PC3_t$, $PC4_t$ and $PC5_t$ are the returns of the first, second, third, fourth and fifth principal component factors, respectively. Inspection of the eigenvalues shows that, on average, the principal component factors jointly explain 65 percent of the variation in the industry returns that is left unexplained by the Fama and French model.[6]

We then allocate stocks to mutually exclusive decile portfolios based on 11-month one-month lagged residual returns relative to the eight-factor model in Equation (2.3). As in our main analysis, we form the deciles using monthly, quarterly, semi-annually and yearly holding periods. We now consider the post-formation returns over the period January 1930 to December 2007 for the return differential between the top and bottom deciles. The results are in Table 2.10.

Interestingly, it appears that ranking stocks on their residual return relative to the Fama and French model augmented with our industry factors helps to further reduce the dynamic exposures momentum strategies: for both one-, three- and six-month holding periods the adjusted R-squared values of the regression model in Equation (2.2) is lower for momentum portfolios formed on residual returns that also incorporate industry effects, compared to the values for portfolios formed on residual returns relative to only the Fama and French factors (see Panel B of Table 2.2). The exposure of the residual momentum strategy to the *RMRF* factor is now statistically and economically not distinguishable from zero. Nonetheless, it does not appear to be the case that taking industry effects into account significantly alters the risks and profits of the residual momentum strategy. For all holding horizons, the Sharpe ratios remain nearly unchanged after incorporating our industry factors in estimating residual stock returns. We therefore conclude that the portion of the risk of momentum that can be attributed to industries and which is not captured by the Fama and French factors is very small.

2.5 Summary and concluding comments

We present a realistic momentum strategy based on residual stock returns that significantly improves upon classic total return momentum strategies, without using hindsight knowledge or instruments that are not available to investors in reality. Our approach begins with estimating residual returns for each stock relative to the Fama and French factors. We find that ranking stocks on their residual returns is a very effective approach to isolate the stock-specific component of momentum. Our results indicate that residual momentum exhibits risk-adjusted profits that are about twice as large as those associated with total return momentum.

[6] As a measure of R-squared we take the ratio between sum of the first five eigenvalues and the total sum of eigenvalues resulting from our PCA at each point in time.

Moreover, the main arguments that have been put forward in the academic literature to rationalize momentum are unsuccessful in explaining residual momentum. First, while total return momentum performs poorly during economic crises, residual momentum displays consistent outperformance under these conditions. Second, unlike total return momentum, residual momentum is not systematically tilted towards small caps stocks with increased levels of firm-specific risk. Third, residual momentum is substantially longer-lived than total return momentum. Fourth, unlike total return momentum, residual momentum is not systematically plagued by seasonal patterns such as the January effect. Fifth, while the profits of total return momentum strategies have been insignificant subsequent to the period after the publication of a large number of academic studies on the momentum anomaly, residual momentum remained remarkably robust over the most recent time period.

Our results add new insights to the literature on the importance of common-factor and stock-specific components for the risks and profits of momentum strategies. We find that roughly 50 percent of the risks and only 25 percent of the profits of total return momentum can be attributed to exposures to the Fama and French factors. We conclude that the common-factor component of total return momentum positively contributes to the profitability of total return momentum. At the same time, a disproportionally large portion of the risk of total return momentum can be attributed to the common-factor component.

Our empirical evidence also contributes to the body of literature that attempts to explain the momentum anomaly by behavioural biases of investors. Barberis, Schleifer and Vishny (1998), Daniel, Hirschleifer and Subrahmanyam (1998), and Hong and Stein (1999) have developed behavioural models that attribute the momentum effect to investors under-reacting to new information and slow information diffusion by financial markets. Our finding that the largest portion of the profits of total return momentum can be attributed to exposures to idiosyncratic factors is supportive of the gradual-formation-diffusion hypothesis of Hong and Stein (1999) that predicts that firm-specific information diffuses only gradually across the investment public. Along these lines, our results are also supportive to the recent finding of Gutierrez and Pirinsky (2007) that investors' under-reaction is more strongly pronounced for firm-specific events than for common events.

Our finding that residual momentum delivers even higher risk-adjusted abnormal returns than total return momentum poses a serious challenge to the Efficient Market Hypothesis and indicates that investors striving to achieve superior returns by engaging in momentum trading are more likely to realize their objectives by ranking stocks on their residual returns than total returns.

3 The Volatility Effect[1]

3.1 Introduction

Efficient markets theory has been challenged by the finding that relatively simple investment strategies are found to generate statistically significantly higher returns than the market portfolio. Well-known examples are the value, size and momentum strategies, for which return premiums have been documented in US and international stock markets. Market efficiency is also challenged, however, if some simple investment strategy generates a return similar to that of the market, but at a systematically lower level of risk.

An interesting study in this regard is the empirical analysis of the characteristics of minimum variance portfolios in Clarke, de Silva and Thorley (2006), henceforth CST. These authors find that minimum variance portfolios, based on the 1,000 largest US stocks over the 1968-2005 period, achieve a volatility reduction of about 25%, whilst delivering comparable, or even higher, average returns than the market portfolio. We present a simple alternative approach to constructing portfolios with similar risk and return characteristics. Specifically, we create decile portfolios that are based on a straightforward ranking of stocks on their historical return volatility. Contrary to CST, we effectively only use the diagonal of the historical covariance matrix with this approach. We find that portfolios consisting of stocks with the lowest historical volatility are associated with Sharpe ratio improvements which are even larger than those in CST, and statistically significant positive alpha.

A related study in this regard is Ang, Hodrick, Xing and Zhang (2006), who report that US stocks with high volatility earn abnormally low returns over the 1963-2000 period. These authors focus on a very short term (1 month) volatility measure, while in our study we concentrate on long-term (past 3 years) volatility, which implies a much lower portfolio turnover. Furthermore, we do not only find that high risk stocks are exceptionally unattractive, but also that low risk stocks are particularly attractive.

Ranking stocks on their historical volatility bears a resemblance to ranking stocks on their historical CAPM beta. Theoretically this follows from the fact that the beta of a stock is equal to its correlation with the market portfolio times its historical volatility and divided by the volatility of the market portfolio. Empirically we also observe that

[1] This chapter is based on Blitz and van Vliet (2007). We would like to thank Willem Jellema for programming assistance and appreciate the comments of Thierry Post, Gerben de Zwart and Laurens Swinkels.

portfolios consisting of stocks with a low (high) volatility exhibit a low (high) beta as well. Since the earliest tests of the CAPM researchers have shown that the empirical relation between risk and return is too flat, e.g. Fama and MacBeth (1973). Similarly, others such as Black, Jensen and Scholes (1972) report that low beta stocks contain positive alpha. In their seminal paper, Fama and French (1992) show that beta does not predict return in the 1963-1990 period, especially after controlling for size. In our sample we also find alpha for portfolios ranked on beta, but considerably less than for portfolios ranked on volatility.

Our main contributions to the existing literature are as follows. Firstly, we document a clear volatility effect: low risk stocks exhibit significantly higher risk-adjusted returns than the market portfolio, while high risk stocks significantly underperform on a risk-adjusted basis. Secondly, our findings are not restricted to the US stock market, but apply to both the global and regional stock markets. The alpha spread of the top versus bottom decile portfolio amounts to 12% per annum for our universe of global large-cap stocks over the 1986-2006 period. Thirdly, we compare the volatility effect with the classic size, value and momentum strategies and control for these effects. In order to disentangle the volatility effect from those other effects we use global and local Fama and French regressions and apply a double sorting methodology. We find that the volatility effect is in fact a separate effect, and of comparable magnitude. Fourthly, we provide possible explanations for the success of the strategy which include leverage restrictions, inefficient industry practice or behavioral biases among private investors, which all flatten the risk-return relation. Finally, we argue that benefiting from the low volatility effect in reality is not easy, as long as institutional investors do not include low risk stocks as a separate asset class in their strategic asset allocation process.

The remainder of this paper is organized as follows. In the following section we first describe our data and methodology. Our primary focus is on a universe of global large-cap stocks. Subsequently, we present results for the US, European and Japanese markets in isolation. In the next section we control for other cross-sectional effects, again tested on global and regional markets separately. This is followed by a discussion of possible explanations for the superior Sharpe ratios of low risk portfolios. We end with our conclusions and implications for investors.

3.2 Data and methodology

At the end of every month, starting in December 1985 and ending in January 2006, we identify all constituents of the FTSE World Developed index and take these as our universe for that particular month. This global large-cap universe consists of approximately 2,000 stocks on average; the actual number varying between about 1,500 and 2,400 over time. Many return irregularities are known to disappear or become significantly less pronounced when the universe is restricted to large-caps, which makes our choice of universe conservative.

Our data sources are Factset for FTSE index constituent and return data, Compustat for US fundamental data, Worldscope for non-US fundamental data and Thomson Financial Datastream for short-term interest rate data. Short-term interest rates are used for converting local stock returns to local stock returns in excess of their local risk free return.[2] Returns are log-transformed in order to make them additive over time. The log-transformed excess returns are used throughout our analysis for all return calculations.

At the end of each month we construct equally weighted[3] decile portfolios by ranking stocks on the past 3 year volatility of weekly returns. We also rank stocks on their book-to-market ratio (valuation), past 12 minus 1 month total return (momentum) and free float market value (size). For the volatility and size measures, stocks with the lowest scores are assigned to the top decile, while for the valuation and momentum strategies stocks with the highest factor scores are the preferred ones. Factor scores are compared directly across all stocks, without imposing sector or country restrictions. As a result, the entire Japanese market may be unattractive on valuation at the height of the Japan bubble during the late eighties. We do control for regional effects by presenting results for the US, Europe and Japan markets in isolation. Portfolios are rebalanced with a monthly frequency and transaction costs are ignored throughout our analysis.

For each decile portfolio we calculate the return (in excess of the local risk-free return) over the month following portfolio formation. For the resulting time series of returns we calculate both the average, standard deviation and Sharpe ratio. In order to test for the statistical significance of the difference between two Sharpe ratios, we apply the Jobson and Korkie (1981) test with the Memmel (2003) correction. This test statistic is calculated according to the formula below and asymptotically follows a standard normal distribution. Here SR_i refers to the Sharpe ratio of portfolio i, $\rho_{i,j}$ to the correlation between portfolios i and j, and T to the number of observations.

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[2] Note that using these returns is equivalent to assuming that first all currency risk is hedged to whichever base currency, and next converting these currency hedged stock returns to excess returns, by subtracting the risk free return of the chosen base currency.

[3] All results presented in this paper are based on equally weighted portfolios. For cap-weighted portfolios we found similar results, but these are not presented for the sake of brevity.

$$z = \frac{SR_1 - SR_2}{\sqrt{\frac{1}{T}\left[2(1-\rho_{1,2}) + \frac{1}{2}(SR_1^2 + SR_2^2 - SR_1 SR_2(1+\rho_{1,2}^2))\right]}} \tag{3.1}$$

We employ both a regression based methodology and a double-sorting methodology in order to disentangle the volatility effect from other effects. We use the portfolios sorted on size and book-to-market in order to construct global and regional Fama-French equivalent hedge factors. We define SMB (small-minus-big) and HML (high-minus-low book-to-market) as the return difference between the top 30% and the bottom 30% ranked stocks. By regressing the return of volatility sorted portfolios on these factors we control for possible systematic exposures to SMB and HML. Additionally, we apply a double-sorting routine, where stocks are first ranked on size or book-to-market and subsequently on volatility within the size or book-to-market buckets. This is an empirically robust way to control for implicit loadings on these factors.

Fama-French adjusted alphas are estimated using the following equation:

$$R_i = \alpha_i + \beta_i R_m + s_i SMB + h_i HML + \varepsilon_i \tag{3.2}$$

Here R_i is the return on decile portfolio i, R_m is the excess return on the global market portfolio defined as the equally weighted average of all stocks, β_i, s_i and h_i are the estimated factor exposures and α_i is the Fama-French adjusted alpha. Single factor CAPM-adjusted alphas are calculated by including only the R_m factor in the regression. Statistical significance of the alphas is obtained in the straightforward manner from the regression.

3.3 Results

3.3.1 Results by region

Table 3.1 contains an overview of our main results on the full, global universe, for the decile portfolios ranked on past 3 year volatility. The top decile portfolio, which contains the low risk stocks, can be seen to generate returns which are slightly above average. In general, however, the relation between historical volatility and subsequent return appears to be rather weak, except for a large underperformance of the bottom decile portfolios, i.e. the high risk stocks. The difference in average return between the top and bottom decile portfolio equals 5.9%.

Table 3.1

Main results global decile portfolios based on historical volatility

This table shows the return and risk characteristics of decile portfolios based on sorting stocks on their historical (past 3-year) volatility. The sample consists of FTSE World Developed index constituents over the period December 1985 until January 2006.

Panel A: Decile portfolios based on historical return volatility

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-10	Univ
Excess return	7.3%	7.1%	8.0%	6.2%	5.0%	5.6%	5.6%	7.2%	3.4%	1.4%	5.9%	6.0%
Standard deviation	10.1%	12.6%	13.6%	14.0%	14.0%	15.1%	16.5%	17.7%	20.4%	27.5%	23.7%	15.0%
Sharpe ratio	0.72	0.57	0.59	0.44	0.36	0.37	0.34	0.41	0.17	0.05		0.40
(t-value)	(2.21)	(1.60)	(2.02)	(0.76)	(-0.65)	(-0.51)	(-1.13)	(0.18)	(-2.83)	(-2.70)		-
Beta	0.56	0.75	0.84	0.90	0.90	0.98	1.07	1.13	1.29	1.58	-1.02	1.00
Alpha	4.0%	2.6%	3.0%	0.9%	-0.4%	-0.3%	-0.7%	0.4%	-4.3%	-8.0%	12.0%	-
(t-value)	(3.12)	(2.16)	(2.60)	(1.03)	(-0.44)	(-0.32)	(-1.01)	(0.42)	(-2.94)	(-2.61)	(2.96)	-

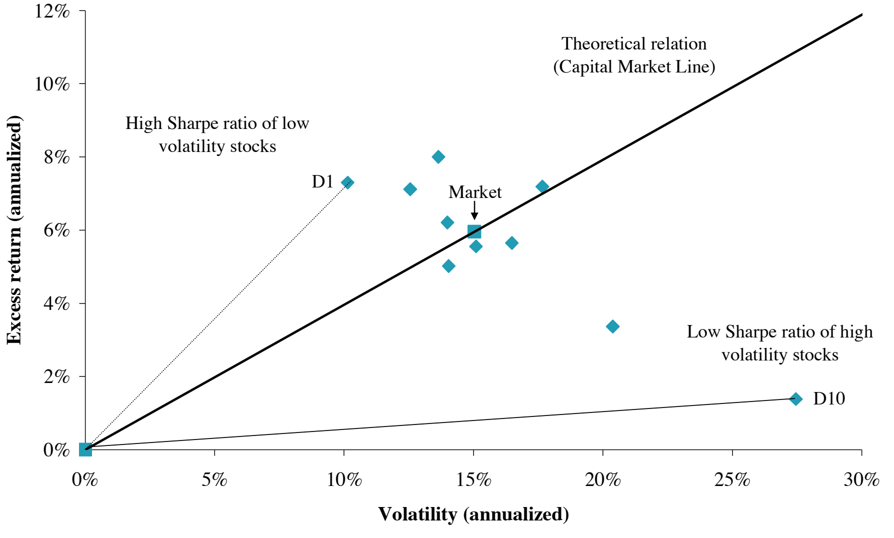
Panel B: Risk analysis of portfolios based on historical volatility

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-10	Univ
Return up	-1.1%	-0.7%	-0.3%	-0.3%	-0.4%	-0.2%	0.2%	0.5%	0.6%	1.4%	-2.5%	0.0%
Return down	1.8%	1.2%	0.9%	0.5%	0.4%	0.2%	-0.4%	-0.5%	-1.5%	-2.9%	4.8%	0.0%
Max drawdown	-26%	-32%	-33%	-36%	-46%	-41%	-40%	-43%	-67%	-86%	-	-38%

Figure 3.1

Empirical versus theoretical relation between volatility and return

This graph visualizes the empirical relation between volatility and return for decile portfolios based on sorting stocks on their historical (past 3-year) volatility. For comparison, we also show the theoretical Capital Market Line.



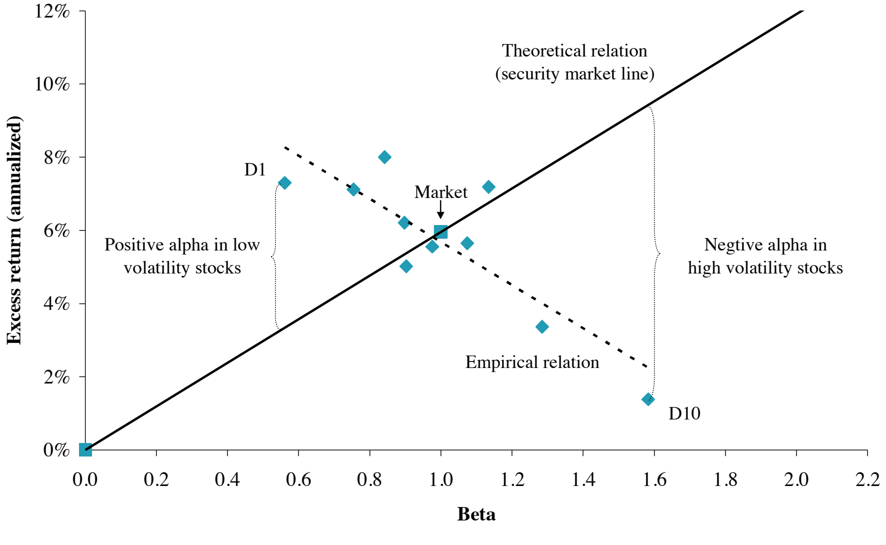
The results become more interesting when we shift to a risk-adjusted performance perspective instead of looking at straight returns. Ex post standard deviations can be seen to increase monotonically for the consecutive decile portfolios. The volatility of the top decile (D1) portfolio is only about two thirds that of the market portfolio. Note that this volatility reduction is even larger than the one found by CST (2006) for (US) minimum variance portfolios. At the other end we have the bottom decile (D10) portfolio, with a standard deviation which is almost double that of the market portfolio. Combined with its low return, this results in a very low Sharpe ratio for the high risk stock portfolio. Because the other volatility decile portfolios exhibit relatively small differences in average returns, their Sharpe ratios are driven primarily by the standard deviation in the denominator. One of our key findings is that the top decile of low risk stocks achieves a Sharpe ratios of 0.72, compared to a Sharpe ratio of only 0.40 for the market portfolio. This difference in Sharpe ratios is statistically significant at the 5% level. The Sharpe ratios show a steadily declining pattern across the volatility sorted portfolios, with the Sharpe ratio of the bottom decile portfolio being significantly lower (at the 5% level again) than the Sharpe ratio of the market portfolio. Thus, we observe a clear relation between ex ante volatility and ex post risk-adjusted returns. A graphic illustration of these findings is given in Figure 3.1.

The next two rows contain the estimated beta and alpha from a CAPM style regression of monthly decile portfolio returns on monthly returns of the market. This analysis shows that the low risk portfolio combines a very low beta of 0.56 with a positive alpha of 4.0% per annum, which is statistically significantly different from zero at the 1% significance level. The betas increase monotonically for the consecutive decile portfolios, suggesting that volatility and beta are related risk measures. The bottom decile portfolio consisting of the highest risk stocks exhibits an estimated beta of 1.58 and a negative alpha of 8.0% per annum. This finding implies a negative relation between risk and return. The combined alpha spread for the low risk minus high risk portfolio amounts to 12.0%. A graphic illustration of these findings is given in Figure 3.2. The risk/return characteristics of the volatility sorted portfolios can be seen to be in clear violation of the theoretical (CAPM) security market line.

Figure 3.2

Empirical versus theoretical relation between beta and return

This graph visualizes the empirical relation between beta and return for decile portfolios based on sorting stocks on their historical (past 3-year) volatility. For comparison, we also show the theoretical Security Market Line.



Panel B of Table 3.1 displays additional characteristics of the volatility decile portfolios. The first two rows contain a breakdown of the returns of the ten volatility portfolios with regard to up market months versus down market months. The low risk portfolios can be seen to underperform the market during up market months, while outperforming the market during down market months. This behavior is consistent with the low beta of the low risk portfolios observed before. Importantly, the underperformance during up months is considerably smaller than the outperformance during down months, although this effect is countered to some degree by the more frequent occurrence of up months (59%, versus 41% down months). The high risk portfolios exhibit precisely the opposite behavior: outperformance during up months, but not enough to offset the underperformance during down months. The third row in Panel B contains maximum drawdown statistics, defined as the maximum loss which an investor in these portfolios could have been confronted with (worst entry and worst exit moments). Just like the volatility of the low risk portfolios is only about two thirds that of the market, so are their maximum drawdowns, at 26% for the top decile portfolio versus over 38% for the market. As one would expect, the largest drawdowns (exceeding 80%!) are experienced by the high risk portfolios.

In Table 3.2 we split the twenty year sample period into two ten year sub samples. The low volatility top decile portfolios exhibit the highest Sharpe ratios in both sub periods. The alpha spread is significant in both the 1985-1995 and 1996-2005 periods. Furthermore, the strength of the effect does not appear to be diminishing over time, as the level and spread of the Sharpe ratios and alphas is in fact larger during the more recent sub period.

3.3.2 Results by region

An inspection of the composition of the low risk portfolio over time suggests a pronounced ‘anti-bubble’ behavior. The strategy avoids the two main bubbles which occurred during our sample period: the Japan bubble in the late eighties and the TMT bubble in the late nineties. Avoiding these bubbles initially results in underperformance, but after the bubbles burst the low risk portfolios tend to do particularly well. The underweight of Japan is in fact the most significant country bet of the strategy, with the US being the main beneficiary of the weight that needs to be redistributed. Note that during more recent years the underweight of Japan has gradually disappeared. At the sector level the strategy tends to systematically overweight sectors such as utilities and real estate, while a typical high risk sector such as IT is usually avoided by the strategy. For some other sectors the position taken by the strategy varies considerably over time. For example, the low risk

Table 3.2

Sub period analysis of global decile portfolios based on historical volatility

This table shows the return and risk characteristics of decile portfolios based on sorting stocks on their historical (past 3-year) volatility during the first half and second half of the sample. The sample consists of FTSE World Developed index constituents over the period December 1985 until January 2006.

Panel A: Jan 1986 through Dec 1995

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-10	Univ
Excess return	5.9%	6.1%	7.0%	4.4%	1.5%	3.0%	4.4%	5.4%	2.9%	1.7%	4.1%	4.4%
Standard deviation	11.9%	14.5%	15.5%	15.8%	14.8%	15.9%	17.5%	18.5%	19.3%	20.6%	13.7%	15.8%
Sharpe ratio	0.49	0.42	0.45	0.28	0.10	0.19	0.25	0.29	0.15	0.08		0.28
Alpha	2.9%	2.3%	2.9%	0.1%	-2.4%	-1.2%	-0.4%	0.4%	-2.2%	-3.6%	6.5%	0.0%

Panel B: Jan 1996 through Jan 2006

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-10	Univ
Excess return	8.7%	8.1%	9.0%	8.0%	8.5%	8.1%	6.9%	9.0%	3.9%	1.0%	7.7%	7.5%
Standard deviation	8.0%	10.3%	11.5%	11.9%	13.3%	14.2%	15.4%	16.8%	21.5%	33.0%	30.6%	14.3%
Sharpe ratio	1.09	0.79	0.78	0.67	0.64	0.57	0.45	0.53	0.18	0.03		0.53
Alpha	5.7%	3.5%	3.6%	2.0%	1.7%	0.8%	-1.0%	0.4%	-6.9%	-14.2%	19.8%	0.0%

portfolio initially contains a significant number of telecom stocks. During the TMT bubble stocks from the telecom sector are avoided however, only to make a reappearance during the final years of our sample period.

In order to verify that the low risk anomaly is not the result of some systematic regional bets we now turn to the results on a regional basis. This analysis also sheds light on the robustness of the strategy. Panels A, B and C of Table 3.3 contain the main results for respectively the US, European and Japanese markets in isolation, structured in the same way as Table 3.1 for the global universe. The volatility effect turns out to be very persistent over the three regions, the regional results being similar to the results on a global basis.

For all three regions there is not much evidence of anomalous behavior of the volatility portfolios if we take a simple return perspective, except for a large underperformance of the bottom decile, i.e. the high risk stocks. For the US market we even find that the top decile of low risk stocks underperforms relative to the market. However, just like in the global analysis, the picture at the regional level changes dramatically if we take a risk-adjusted return perspective. All ex post standard deviations and betas increase monotonically for the consecutive volatility decile portfolios. Within each of the three regions the volatility of the top decile portfolios is only about 70% of the volatility of the market. The bottom decile portfolios are consistently at the other extreme end, featuring standard deviations that are at least 50-100% higher than those of the market. Combined with the very low returns of these portfolios, this results in Sharpe ratios which are negative or close to zero. On the other hand, the top decile portfolios of low risk stocks exhibit Sharpe ratios which are well above those of the market. The Sharpe ratio improvement is biggest in Europe (Sharpe ratio of over 0.49 for the low risk portfolio versus 0.28 for the market), followed by Japan (0.34 versus 0.18) and lastly the US (0.58 versus 0.47). For each region the Sharpe ratio of the high risk bottom decile portfolio is lower than that of the market with statistical significance at the 1% level.

The alpha spread is very consistent across the 3 main regions, varying from 10.2% for Europe to 13.8% for the US. The regional alpha spreads are of comparable magnitude as the alpha spread at the global level (12.0%), which implies that bottom-up regional allocation is not the key driver for the global results. The alpha spreads are statistically significantly different from zero at the 5% level for the US and Japan, and even at the 1% level for Europe.

Table 3.3

Regional results

This table shows the return and risk characteristics of decile portfolios based on sorting stocks on their historical (past 3-year) volatility for the US, Europe and Japan separately. The sample consists of FTSE World Developed index constituents over the period December 1985 until January 2006.

Panel A: Main results US

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-10	Univ
Excess return	6.9%	7.6%	8.1%	8.9%	8.3%	8.9%	9.6%	6.3%	7.0%	3.8%	3.1%	8.1%
Standard deviation	12.0%	13.7%	15.4%	15.9%	17.0%	16.7%	18.0%	20.7%	25.8%	36.5%	35.0%	17.1%
Sharpe ratio	0.58	0.56	0.53	0.56	0.49	0.53	0.53	0.30	0.27	0.10		0.47
(t-value)	(0.51)	(0.70)	(0.57)	(0.89)	(0.19)	(1.00)	(0.90)	(-2.55)	(-2.13)	(-2.57)		-
Beta	0.45	0.70	0.82	0.86	0.94	0.95	1.01	1.16	1.39	1.77	-1.32	1.00
Alpha	3.3%	1.9%	1.5%	1.9%	0.7%	1.1%	1.4%	-3.2%	-4.3%	-10.6%	13.8%	0.0%
(t-value)	(1.57)	(1.30)	(1.06)	(1.38)	(0.54)	(1.31)	(1.25)	(-2.60)	(-1.92)	(-2.30)	(2.29)	-

Table 3.3 (continued)

Panel B: Main results Europe

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-10	Univ
Excess return	6.0%	6.9%	6.3%	6.8%	5.2%	4.7%	3.5%	2.4%	3.7%	0.0%	6.0%	4.9%
Standard deviation	12.4%	14.2%	15.1%	16.9%	17.2%	17.8%	19.0%	20.2%	23.7%	28.7%	21.6%	17.5%
Sharpe ratio	0.49	0.49	0.42	0.40	0.31	0.27	0.19	0.12	0.16	0.00		0.28
(t-value)	(1.95)	(2.12)	(1.79)	(1.78)	(0.45)	(-0.16)	(-1.85)	(-2.71)	(-1.65)	(-2.67)		-
Beta	0.64	0.74	0.82	0.93	0.94	0.98	1.06	1.12	1.29	1.49	-0.85	1.00
Alpha	2.9%	3.3%	2.4%	2.3%	0.7%	0.0%	-1.6%	-3.0%	-2.6%	-7.3%	10.2%	0.0%
(t-value)	(2.44)	(2.61)	(2.14)	(2.10)	(0.63)	(0.01)	(-1.83)	(-2.88)	(-1.54)	(-2.73)	(2.92)	-

Panel C: Main results Japan

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-10	Univ
Excess return	5.1%	5.1%	3.0%	4.6%	4.8%	4.2%	4.7%	3.5%	1.6%	-2.3%	7.5%	3.8%
Standard deviation	15.2%	18.0%	19.6%	20.1%	21.5%	22.3%	23.2%	25.3%	27.1%	33.0%	25.5%	21.5%
Sharpe ratio	0.34	0.28	0.15	0.23	0.22	0.19	0.20	0.14	0.06	-0.07		0.18
(t-value)	(1.31)	(1.25)	(-0.34)	(0.92)	(0.93)	(0.28)	(0.60)	(-0.73)	(-1.70)	(-2.62)		-
Beta	0.61	0.78	0.87	0.91	0.98	1.02	1.06	1.15	1.21	1.42	-0.81	1.00
Alpha	2.8%	2.1%	-0.3%	1.2%	1.1%	0.4%	0.7%	-0.8%	-2.9%	-7.7%	10.5%	0.0%
(t-value)	(1.62)	(1.46)	(-0.23)	(1.04)	(1.04)	(0.36)	(0.69)	(-0.66)	(-1.67)	(-2.76)	(2.52)	-

3.3.3 Controlling for other effects

How does the volatility effect relate to other effects, which have been documented in previous research? For example, could it be that the low-volatility portfolio contains a high proportion of value stocks, and that as a result of this it is simply capturing the value premium? And how does the magnitude of the volatility effect compare to classic effects such as value, size and momentum?

In order to answer these questions we first turn to Table 3.4, which contains the same statistics as we saw before for the low volatility portfolios, but now for the classic value, momentum and size strategies (as defined earlier). Consistent with previous research, we find that the top deciles of the value and momentum strategies outperform relative to the equally weighted universe, while the bottom deciles underperform. However, we find little evidence of a size effect within our sample of FTSE World Developed index constituents.

Interestingly, the low volatility top decile portfolio delivers a higher return per unit of risk (Sharpe ratio) than each individual value, momentum and size decile portfolios. From an alpha perspective the volatility effect ranks second out of four, only the momentum effect being somewhat stronger in our sample. Based on this analysis we conclude that the volatility effect holds out well in terms of magnitude, and thus economic relevance, in comparison to other classic effects.

A comparison of the characteristics of the volatility decile portfolios to the other decile portfolios suggests that the low volatility effect does indeed constitute a separate effect. For example, the top decile portfolios on value, size and momentum exhibit a volatility which is higher than that of the market, while the volatility of the low volatility portfolio is only about two thirds of that of the market. Also, the betas of the value, size and momentum top decile portfolios are close to, or even above 1, while the low volatility top decile portfolio exhibits a beta of only 0.56. These very different characteristics suggest that the low volatility effect is a distinct effect, and not some classic effect in disguise.

Table 3.5 further separates the volatility effect from the other effects by means of Fama-French (FF) regressions. Panel A shows the alphas by correcting for value and size using a global Fama-French factor model. We find that one third of the global alpha spread of 12.0% can be attributed to size and value exposures. The 8.1% alpha which remains is thus not related to value and/or size and is left unexplained. Panel B shows the results of similar analyses at the regional level, based on local Fama-French regressions. The FF-

Table 3.4

Comparison with other investment strategies

This table shows the return and risk characteristics of decile portfolios based on sorting stocks on size (market capitalization), value (book-to-market ratio) or momentum (past 12-1 month return). The sample consists of FTSE World Developed index constituents over the period December 1985 until January 2006.

Panel A: Decile portfolios based on Size (market capitalization)

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-10	Univ
Excess return	5.4%	7.6%	6.3%	6.7%	5.8%	5.5%	6.5%	5.6%	4.4%	4.5%	0.9%	6.0%
Standard deviation	18.5%	15.6%	16.1%	15.9%	15.9%	15.8%	15.3%	14.7%	15.2%	15.2%	13.4%	15.0%
Sharpe ratio	0.29	0.49	0.39	0.42	0.36	0.35	0.43	0.38	0.29	0.30		0.40
(t-value)	(-0.98)	(1.13)	(-0.12)	(0.56)	(-0.73)	(-1.03)	(0.53)	(-0.32)	(-1.28)	(-0.92)		-
Beta	1.10	0.98	1.03	1.03	1.04	1.03	0.98	0.95	0.95	0.90	0.20	1.00
Alpha	-1.1%	1.7%	0.1%	0.6%	-0.4%	-0.6%	0.7%	-0.1%	-1.2%	-0.9%	-0.3%	0.0%
(t-value)	(-0.62)	(1.50)	(0.11)	(0.77)	(-0.60)	(-0.90)	(0.77)	(-0.12)	(-1.04)	(-0.56)	(-0.10)	-

Table 3.4 (continued)

Panel B: Decile portfolios based on Value (book-to-market)

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-10	Univ
Excess return	9.3%	9.5%	8.8%	7.3%	4.8%	4.8%	3.8%	3.9%	4.0%	2.0%	7.3%	6.0%
Standard deviation	20.0%	16.1%	15.0%	14.4%	15.0%	15.2%	15.0%	15.5%	15.9%	16.8%	14.4%	15.0%
Sharpe ratio	0.46	0.59	0.59	0.50	0.32	0.32	0.25	0.25	0.25	0.12		0.40
(t-value)	(0.65)	(2.43)	(2.61)	(1.79)	(-1.52)	(-1.39)	(-2.63)	(-2.24)	(-1.75)	(-2.33)		-
Beta	1.20	1.02	0.95	0.93	0.97	0.98	0.98	0.99	0.99	0.98	0.22	1.00
Alpha	2.1%	3.4%	3.1%	1.7%	-1.0%	-1.0%	-2.0%	-2.0%	-1.9%	-3.9%	6.0%	0.0%
(t-value)	(1.10)	(3.06)	(3.28)	(2.17)	(-1.43)	(-1.25)	(-2.76)	(-2.22)	(-1.56)	(-2.14)	(1.91)	-

Panel C: Decile portfolios based on Momentum (12-1M)

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-10	Univ
Excess return	12.1%	8.6%	8.7%	6.1%	6.0%	5.1%	3.9%	2.5%	1.8%	0.9%	11.2%	5.9%
Standard deviation	17.5%	14.9%	13.7%	13.7%	13.6%	14.0%	14.5%	16.4%	19.4%	27.0%	24.0%	15.0%
Sharpe ratio	0.69	0.58	0.63	0.44	0.44	0.36	0.27	0.15	0.09	0.03		0.39
(t-value)	(2.05)	(1.71)	(2.52)	(0.71)	(0.90)	(-0.50)	(-2.12)	(-3.10)	(-2.97)	(-2.52)		-
Beta	0.96	0.89	0.85	0.87	0.88	0.90	0.94	1.05	1.19	1.49	-0.53	1.00
Alpha	6.5%	3.4%	3.7%	1.0%	0.9%	-0.2%	-1.6%	-3.6%	-5.2%	-7.9%	14.3%	0.0%
(t-value)	(2.92)	(2.30)	(3.26)	(1.03)	(1.17)	(-0.32)	(-2.10)	(-3.35)	(-3.07)	(-2.33)	(2.82)	-

adjustment has the biggest impact for the US, where the alpha drops from 13.8% to 7.0%. For Europe the alpha is lowered to 7.4% from 10.2%. The alpha is least affected for Japan, at 9.8% versus 10.5%. From these results we can conclude that the volatility effect is reduced, but does not disappear after applying the FF-adjustment.

The FF-adjustment is based on a single regression, which is applied ex post to the time series of returns. Thus, the factor exposures are estimated and assumed to be constant over time. An alternative way to disentangle the volatility effect from other cross-sectional effect is to apply a double sorting approach. This is a robust, non-parametric technique which enables us to systematically neutralize other effects ex ante. Panel A of Table 3.6 contains the results of a double sort on value followed by volatility. Every month stocks are first grouped into five quintiles based on value (book-to-market). Next we create decile portfolios based on volatility within each of these value quintiles. Finally, a value neutral top decile volatility portfolio is constructed by combining the five top decile volatility portfolios from within each value quintile (and similarly for the other decile portfolios). Panels B contains similar results for a double sort on size followed by volatility, and Panel C for a double sort on momentum followed by volatility.

The volatility effect turns out to be robust to the ex ante factor neutralizations of the double sorts. The global (CAPM-)alpha remains at 8.9% or higher, and the alpha for the US at 9.5% or higher. Only for Europe we find that the alpha drops to 6.4%, in case of the momentum double sort, and for Japan to 6.6%, in case of the value double sort. Again we conclude that classic effects at most explain only part of the volatility effect.

3.3.4 Robustness tests

The volatility effect is robust to a different measurement period for volatility. Panel A of Table 3.7 shows the CAPM-alphas of decile portfolios based on 1 year instead of 3 year weekly historical return volatility. The top versus bottom decile alpha spread is slightly lower in a global context (11.2% versus 12.0%), but can be seen to increase somewhat for both the US and Europe. Only for Japan the alpha spread drops by a relatively large amount, from 10.5% to 7.1%.

We also compare the volatility effect with the classic beta effect, as described in the introduction. Contrary to volatilities, estimated betas are sensitive to the choice of the market portfolio. Beta can for example be estimated relative to a global index, but also relative to a regional index. This is an important empirical issue. For example, the Japanese market has shown a low correlation with the global stock market, which ceteris paribus

Table 3.5

Global and regional Fama-French corrected alphas

This table shows the raw and Fama-French adjusted alphas of our decile portfolios based on sorting stocks on their historical (past 3-year) volatility. The sample consists of FTSE World Developed index constituents over the period December 1985 until January 2006.

Panel A: Fama-French corrected alphas

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-10
Global Alpha	4.0%	2.6%	3.0%	0.9%	-0.4%	-0.3%	-0.7%	0.4%	-4.3%	-8.0%	12.0%
FF-Alpha	2.8%	1.3%	1.8%	0.3%	-0.8%	-0.3%	-0.6%	1.2%	-2.9%	-5.4%	8.1%

Panel B: Regional Fama-French corrected alphas

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-10
US	3.3%	1.9%	1.5%	1.9%	0.7%	1.1%	1.4%	-3.2%	-4.3%	-10.6%	13.8%
FF-Alpha	1.3%	0.6%	0.2%	1.0%	0.3%	0.8%	1.0%	-2.8%	-2.9%	-5.7%	7.0%
Europe	2.9%	3.3%	2.4%	2.3%	0.7%	0.0%	-1.6%	-3.0%	-2.6%	-7.3%	10.2%
FF-Alpha	3.2%	3.0%	1.9%	1.9%	0.3%	-0.5%	-2.3%	-3.8%	-2.1%	-4.2%	7.4%
Japan	2.8%	2.1%	-0.3%	1.2%	1.1%	0.4%	0.7%	-0.8%	-2.9%	-7.7%	10.5%
FF-Alpha	2.1%	1.9%	0.1%	1.2%	0.5%	0.0%	0.7%	-0.5%	-1.7%	-7.7%	9.8%

results in lower estimated betas relative to a global index for all Japanese stocks. In order to avoid this issue and in order to have comparable results with other (US) studies, we concentrate on beta sorted portfolios at the regional level.

In Panel B of Table 3.7 we compare the CAPM alphas of portfolios sorted on 3 year historical volatility with those of portfolios sorted on 3 year historical beta, again calculated using weekly return data. For each region we find a clear beta effect. However, the alpha spreads of the beta sorted portfolios are about 3-7 percent smaller for each region, and the alpha patterns are more irregular than those for the volatility sorted portfolios. Therefore, we conclude that the volatility effect is a stronger and less ambiguously defined effect than the beta effect.

Further evidence supporting this conclusion is given in Panel C of Table 3.7, which contains results of double sorting first on beta and then on volatility, similar in set-up to the double sorts described before. Although in this way the alpha is partly subsumed, about 7% remains for Europe and Japan and 4% for the US. Thus, even within groups of stocks with similar betas, sorting stocks on volatility helps to capture additional alpha. Thus, the volatility effect cannot be explained by the classic beta effect. Furthermore, this finding suggests that both the idiosyncratic part and systematic part of volatility are mispriced.

3.4 Possible explanations

In this section we discuss several possible explanations for the volatility effect as documented in this paper.

Firstly, leverage is needed in order to take full advantage of the attractive absolute returns of low risk stocks. In theory this is quite straightforward, but in practice many investors are either not allowed or unwilling to actually apply leverage, especially on the scale needed for exploiting this effect. For example, if a low risk stock portfolio has a volatility which is two-thirds of that of the market, 50% leverage needs to be applied in order to obtain the same level of volatility as the market. As a result, the opportunity which is presented by low risk stocks is not easily arbitraged away. Borrowing restrictions were already identified by Black (1972) as an argument for the relatively good performance of low beta stocks.

Leveraged buyout (LBO) private equity funds might constitute a notable exception in this regard, because a key source of return of LBO funds is the application of leverage to the balance sheets of the companies in which they invest. Thus, the success of

Table 3.6

Double sorted results

This table shows the alpha of decile portfolios based on a double-sorting procedure. Every month stocks are first grouped into five quintiles based on value (book-to-market), size (market capitalization) or momentum (past 12-1 month return). Next we create decile portfolios based on historical (past 3-year) volatility within each of these quintiles. Value, size or momentum neutral volatility decile portfolios are constructed by combining the five corresponding decile volatility portfolios from within each value, size or momentum quintile.

Panel A: Alpha from double sort on value (book/market) and volatilty (past 3 years)

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-10
Global	3.5%	3.0%	2.5%	0.6%	0.4%	-0.1%	-1.1%	-0.6%	-3.1%	-7.6%	11.1%
US	3.4%	1.7%	2.3%	2.4%	1.2%	-0.5%	0.3%	-0.9%	-5.7%	-9.4%	12.7%
Europe	2.4%	3.7%	2.7%	0.9%	0.7%	0.1%	-0.6%	-3.0%	-2.1%	-7.3%	9.7%
Japan	1.3%	0.5%	0.5%	0.8%	1.0%	0.2%	-0.8%	0.7%	-1.8%	-5.3%	6.6%

Panel B: Alpha from double sort on size (market cap) and volatilty (past 3 years)

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-10
Global	3.9%	2.4%	2.6%	1.6%	0.4%	-1.5%	0.7%	-1.6%	-2.9%	-8.3%	12.2%
US	3.8%	1.6%	1.6%	2.3%	1.0%	1.3%	-0.7%	-2.6%	-6.0%	-7.8%	11.6%
Europe	2.7%	3.5%	1.4%	0.9%	2.6%	-1.4%	-1.2%	-1.0%	-3.4%	-6.5%	9.2%
Japan	1.5%	2.4%	0.3%	1.6%	0.2%	0.9%	-0.2%	0.5%	-1.0%	-8.7%	10.2%

Table 3.6 (continued)

Panel C: Alpha from double sort on momentum (12-1M) and volatilty (past 3 years)

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-10
Global	2.9%	2.5%	1.5%	0.7%	0.3%	0.3%	-1.1%	-0.5%	-2.0%	-6.0%	8.9%
US	3.0%	2.0%	1.8%	1.6%	-0.6%	0.5%	-0.3%	-0.9%	-4.2%	-6.5%	9.5%
Europe	1.7%	3.0%	1.3%	0.2%	0.7%	1.1%	-1.3%	-1.2%	-2.5%	-4.7%	6.4%
Japan	2.8%	1.3%	0.8%	0.7%	1.0%	0.7%	0.4%	-0.7%	-2.3%	-7.2%	10.1%

Table 3.7

Robustness tests

This table shows the results of various robustness tests. Panel A shows the alpha of decile portfolios based on past 1-year volatility, Panel B compares the alpha of regional decile portfolios based on past 3-year beta instead of volatility and Panel C shows the alpha from a double-sort on first beta and next past 3-year volatility.

Panel A: CAPM-alpha for decile portfolios sorted on 1 year volatility

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-10
Global	3.1%	2.0%	1.8%	1.4%	-1.1%	-0.5%	-0.3%	0.1%	-1.4%	-8.1%	11.2%
US	4.1%	0.3%	2.3%	2.0%	1.5%	1.6%	1.8%	-4.0%	-5.3%	-10.4%	14.5%
Europe	3.0%	2.7%	1.3%	1.8%	0.7%	0.0%	-0.7%	-1.5%	-1.7%	-8.7%	11.7%
Japan	0.8%	1.3%	2.1%	0.2%	1.3%	0.2%	-0.5%	-0.2%	-2.6%	-6.3%	7.1%

Table 3.7 (continued)

Panel B: CAPM-alpha for decile portfolios sorted on volatility versus beta

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-10
US volatility	3.3%	1.9%	1.5%	1.9%	0.7%	1.1%	1.4%	-3.2%	-4.3%	-10.6%	13.8%
US beta	1.2%	1.7%	1.8%	2.5%	0.2%	1.5%	1.2%	-3.2%	-4.2%	-8.1%	9.3%
Europe volatility	2.9%	3.3%	2.4%	2.3%	0.7%	0.0%	-1.6%	-3.0%	-2.6%	-7.3%	10.2%
Europe beta	1.5%	2.4%	2.8%	0.9%	1.4%	0.7%	-0.7%	-1.8%	-4.1%	-5.9%	7.5%
Japan volatility	2.8%	2.1%	-0.3%	1.2%	1.1%	0.4%	0.7%	-0.8%	-2.9%	-7.7%	10.5%
Japan beta	-1.4%	1.2%	1.1%	1.5%	0.7%	1.3%	1.3%	0.7%	-5.3%	-5.3%	3.8%

Panel C: Alpha from double sort on beta (past 3 years) and volatilty (past 3 years)

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-10
US	2.3%	0.8%	0.8%	0.6%	0.6%	-0.5%	0.2%	-2.9%	-2.4%	-2.1%	4.4%
Europe	2.3%	1.4%	1.5%	1.5%	0.0%	0.7%	-1.3%	-0.2%	-2.9%	-4.8%	7.1%
Japan	2.0%	1.8%	1.6%	0.1%	-1.1%	1.0%	-0.1%	-0.3%	-2.1%	-4.9%	6.9%

LBO private equity investing may, to some degree, be related to the high risk-adjusted returns of low risk stocks. Pure equity investors may be facing practical limitations with regard to leverage, but we want to stress that leverage can be created relatively easily within a balanced portfolio which contains bonds and/or cash next to stocks. Black (1993) already suggested an increased allocation to low risk stocks as an alternative to a given allocation to the market portfolio. For example, instead of investing 50% in traditional stocks and 50% in bonds, an investor might decide to invest 70% in low risk stocks and 30% in bonds. However, this requires that low risk stocks are included as a separate asset class in the strategic asset allocation process of investors. This is not the case in practice however. At least, not yet.

Secondly, the volatility effect could be the result of an inefficient decentralized investment approach. For example, in the professional investment industry it is common practice that first the CIO or an investment committee makes the asset allocation decision, and in a next stage this capital is allocated to managers who buy securities within the different asset classes. Binsbergen et. al (2008) demonstrate that this approach may result in inefficient portfolios. The problem with benchmark driven investing is that asset managers have an incentive to tilt towards high beta and/or high volatility stocks, as this is a relatively simple way for asset managers to generate above average returns, assuming the CAPM holds at least partially. As a result, these high risk stocks may become overpriced, whilst low risk stocks may become underpriced, which is consistent with the return patterns which we document in this paper. Furthermore, new money tends to flow towards asset classes that do well, and within such asset classes to managers with above average performance. This suggests that for a profit-maximizing asset manager outperformance in up markets may be more desirable than outperformance in down markets. Asset managers may thus be willing to overpay for stocks which outperform in up markets, which tend to be high volatility stocks, and underpay for stocks which outperform in down markets, which tend to be low volatility stocks. In sum, the twin desire for outperformance and cash flow of asset managers may result in inefficient portfolios. A solution may be to integrate the two stage process by giving the asset managers one single benchmark, for example the fund specific liabilities, plus a risk budget to deviate.

Thirdly, the volatility effect may be caused by behavioral biases among private investors. Behavioral portfolio theory describes that private investors think in terms of a two-layer portfolio. Shefrin and Statman (2000) identify a low aspiration layer which is designed to avoid poverty, and a high aspiration layer which is designed for a shot at riches. Suppose that private investors make a rational risk-averse choice in the asset allocation decision (first layer), but become risk-neutral or even risk-seeking within a certain specific asset class (second layer). In this case, investors will overpay for risky stocks which are perceived to be similar to lottery tickets. In this perception, buying many stocks destroys upside potential, while buying a few volatile stocks (wish I had bought Microsoft in the eighties) leaves upside potential intact. This way of thinking is consistent with the finding that most private investors only hold about 1-5 stocks in their portfolio, thereby largely ignoring the diversification benefits that are available within the equity market. Deviations from risk-averse behavior of investors may cause high-risk stocks to be overpriced and low-risk stocks to be underpriced.

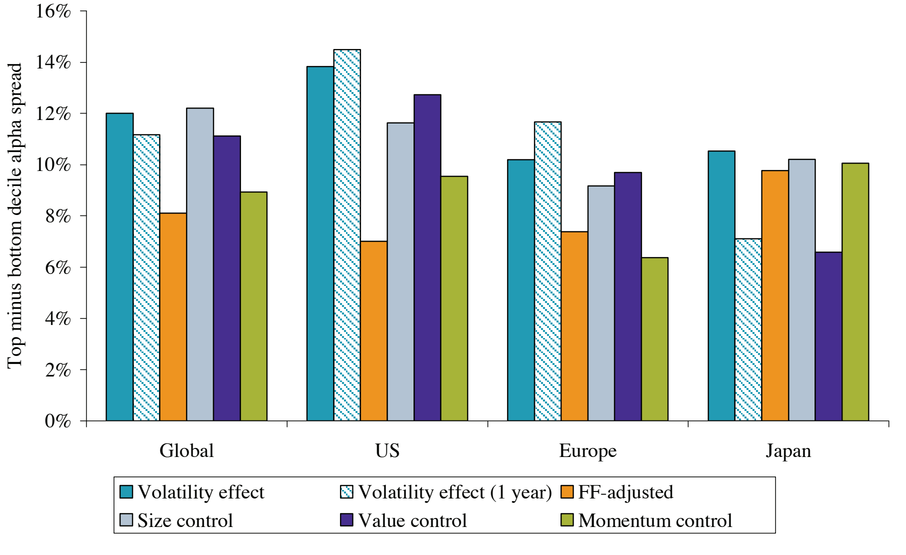
3.5 Conclusion and implications

In this paper we have shown that stocks with low historical volatility exhibit superior risk adjusted returns, both in terms of Sharpe ratios and in terms of CAPM alphas. The volatility effect is similar in size compared to classic effects such as value, size and momentum, and largely remains after Fama-French adjustments and double sorts. A summary of the main results is given in Figure 3.3.

Figure 3.3

Summary of alpha findings

This figure provides a summary of the alphas that were found in our various analyses. The base-case result is the CAPM alpha for a top-minus-bottom decile portfolio based on past (3-year) volatility.



Compared to Clarke et al. (2006), who find significantly lower risk and superior Sharpe ratios for US minimum variance portfolios, our results are stronger, while our approach is easier. Our results are consistent with Ang et al. (2006), who document a large negative alpha for US stocks with high idiosyncratic volatility. However, our results are more symmetric, and based on 3 year instead of 1 month historical volatility, which implies a much lower portfolio turnover.

The volatility effect is particularly strong in a global setting, with a low versus high volatility alpha spread of 12%. The results remain strong however at the regional level (>10%). The low volatility strategy is characterized by relatively small drawdowns, a low beta, outperformance in down markets and underperformance in up markets and anti-bubble behavior. Possible explanations for the success of the strategy include the practical difficulties with arbitraging the effect away due to a need for applying significant leverage, inefficient industry practice or behavioral biases among private investors, which all flatten the risk-return relation.

Exploiting the volatility effect is not easy for benchmark driven equity investors who are facing a relative return objective and are either not allowed or willing to apply leverage. However, for investors interested in high Sharpe ratio investment opportunities such as pension funds, it may be much easier to benefit from the volatility effect, by applying leverage within their asset mix. These investors could simply decide to shift from a given allocation to traditional stocks to a higher allocation to low risk stocks, by reducing the weight of bonds. In order for this option to be taken adequately into account it is essential to include the decision to invest in low risk stocks in the strategic asset allocation process. Therefore, we recommend that absolute return investors distinguish between low risk, high risk and traditional stocks as separate asset classes, just like they distinguish between value versus growth stocks and large-cap versus small-cap stocks in their strategic asset allocation decision making.

4 Fundamental Indexation[1,2]

4.1 Introduction

Arnott, Hsu, and Moore (2005) propose a novel investment approach, which they call fundamental indexation. The main idea behind fundamental indexation, or fundamental indexing, is to create an index in which stocks are weighted by economic fundamentals, such as book value, sales and/or earnings, instead of market capitalization. An important argument put forward by fundamental indexers is that capitalization weighted indices are inferior because they necessarily invests more in overvalued stocks and less in undervalued stocks. However, this is disputed by a.o. Perold (2007), who argues that capitalization weighting does not, by itself, create a performance drag. At present the debate between proponents and critics of fundamental indexing continues to rage on.[3]

In this paper we compare fundamental indices with their traditional cap-weighted counterparts. First we argue that fundamental indices are, essentially, nothing more than a new breed of value indices. Arguably, fundamental indices are more elegant than traditional value indices, but the key underlying idea remains the same. Next we will argue that a fundamental index bears more resemblance to an active investment strategy than to a traditional passive index. Having concluded that a fundamental index is an active value strategy, we next discuss if fundamental indexing is the most efficient way to capture the value premium. We conclude that fundamental indexation is very likely to be inferior compared to more sophisticated quantitative investment strategies.

4.2 Fundamental indices capture the value premium

The weights of stocks in a traditional index are proportional to their market capitalizations. Fundamental indices, however, rather weight stocks in proportion to their economic fundamentals. Thus, weights differences are entirely due to differences in valuation levels, i.e. ratios of fundamental value to market value. For example, if a fundamental index is created based on book values, then the weight differences compared to a market

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[1] Fundamental Indexation is the patent-pending proprietary property and registered trademark of Research Affiliates LLC.
[2] This paper is based on Blitz and Swinkels (2008). The authors thank Thierry Post for valuable comments on an earlier version of this paper.
[3] See for example Arnott & Markowitz (2008), Perold (2008), Treynor (2008) and Hsu (2008), all of which appeared in the March/April 2008 edition of the Financial Analysts' Journal.

capitalization weighted index are entirely due to differences in the book-to-market ratios of the stocks included in the index. In other words, compared to a market capitalization weighted index a fundamental index simply overweights value stocks and underweights growth stocks; a fact which is also recognized by, for example, Asness (2006). This implies that fundamental indices are essentially a new breed of value indices. Of course, value (and growth) indices have been around for many years already, but traditionally these tend to be based on a different, arguably less sophisticated, approach. The traditional approach consists of first classifying each stock as either a value stock or a growth stock, and next creating a value (or growth) index by market capitalization weighting all value (or growth) stocks.[4] Splitting up the universe into two mutually exclusive parts is a rather crude approach compared to fundamental indices, which elegantly re-weight the entire universe of stocks based on fundamental values.

Since the weights differences between a fundamental index and a traditional index are entirely due to differences in valuation levels, any difference in return between a fundamental index and a traditional index must be due to the difference in return between value and growth stocks. Crucially, the proponents of fundamental indexation claim that capitalization weighting by itself introduces a drag on performance, because in a market capitalization weighted index overvalued stocks tend to be overrepresented and undervalued stocks tend to be underrepresented. See for example Arnott et al (2005), Treynor (2005), and Hsu (2006). A fundamentally weighted index is claimed to be superior by avoiding this pitfall. However, Perold (2007) correctly points out that this reasoning hinges critically on the assumption that the mispricing of a stock is, to some extent, predictable by considering the difference between its market price and fundamentals. In other words, the proponents of fundamental indexation assume that stocks with high valuation ratios are more likely to be overvalued than stocks with low valuation ratios. Empirically there is indeed a large amount of evidence for a so-called value premium, as historically value stocks have outperformed growth stocks. This also explains the finding that fundamental indices have outperformed market capitalization weighted indices historically. However, a historical outperformance due to being exposed to an already known return irregularity is something which is quite different from a superior theoretical performance, as a result of avoiding some structural drag on performance that is supposedly associated with capitalization-weighted indices.[5] As Perold (2007) and Kaplan

[4] More recently refinements have been introduced which allow some stocks to be for example 50% value and 50% growth, but the principle has remained the same.

[5] Hemminki and Puttonen (2008) document that fundamental indexation has also generated higher returns in Europe. However, as Asness (2006) points out, this does not come as a surprise, given the

(2008) argue, if we assume that pricing errors are random (in particular, unrelated to valuation ratios), the theoretical case for a systematic outperformance of fundamental indexation breaks down.

We can illustrate the strong value tilt of fundamental indices by regressing the returns of the RAFI 1000 index (the Research Affiliates Fundamental Index for the top 1000 US equities) on the returns of traditional market factor indices. The results of these regressions are displayed in Table 1. We observe that, when we compare the fundamental indexing strategy to the market index, the alpha amounts to 0.19% per month in case we use the Fama-French market factor over the 1962-2005 period, and 0.26% per month in case we use the Russell 1000 index over the 1979-2005 period. Both are highly significant, both from an economical and a statistical point of view. However, these analyses do not take account for the value tilt which characterizes fundamental indexing portfolios. When we add the value and small-capitalization factor of Fama and French (1992), we see that the fundamental indexation strategy has, on average, a large and highly significant (t-statistic over 30) exposure of 0.36 towards the value factor.[6] The loading on the small-capitalization factor is small and negative with -0.07. The results using Russell index data are very similar, with a beta of 0.38 with regard to the Russell 1000 Value/Growth return difference, associated with a highly significant t-statistic of over 30. Thus, these regression results provide strong empirical support for the theoretical observation that fundamental indices are tilted towards value stocks. Particularly interesting is the finding that, after adjusting for this value tilt, the alpha of the RAFI 1000 index drops sharply to an insignificant -0.02% per month in the Fama-French analysis and 0.10% per month, or 1.2% per annum, in case of the Russell data. Thus, we conclude that after adjusting for style exposures, fundamental indexation offers zero, or at best a small positive added value. We can interpret a possible small positive added value positively, namely as evidence that fundamental indexation might constitute a more effective value strategy than traditional value indices. However, the alpha might also simply reflect some hindsight wisdom or biases in the construction of the historical RAFI 1000 returns, which are after all only based on a back-test. Thus, even the small positive alpha might turn out to be an illusion going forward.

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fact that Fama and French (1998) already observe that the value effect is an international phenomenon. Estrada (2008) prefers an international value strategy above an international fundamental indexation strategy.

[6] As the cross-sectional dispersion in fundamental characteristics might change over time, the exposure to the value factor might also be time-varying. We report the long-term average exposure here.

Table 4.1

Regression results

This table shows results of regressions of historical, simulated RAFI 1000 index returns in excess of the risk-free rate of return on two sets of explanatory variables. In Panel A the explanatory variables are the Fama-French market (RMRF), size (SMB) and value (HML) factors. In Panel B the explanatory variables are the Russell 1000 index in excess of the risk-free rate of return and the return difference between the Russell 1000 Value and Russell 1000 Growth indices. Sources: Kenneth French website, Datastream.

Panel A: Fama-French factors, sample period January 1962 - December 2005

	Alpha	RMRF	SMB	HML
CAPM	0.19%	0.91	-	-
	(3.5)	(74.6)	-	-
Fama-French 3-factor	-0.02%	1.02	-0.07	0.36
	(-0.5)	(131.8)	(-7.0)	(30.9)

Panel B: Russell indexes, sample period January 1979 - December 2005

	Alpha	R1000 - risk free	R1000 Value - R1000 Growth
Market-factor only	0.26%	0.91	-
	(3.8)	(59.7)	-
Market and value factor	0.10%	1.01	0.38
	(2.9)	(120.8)	(30.6)

4.3 Fundamental indices resemble active strategies

A fundamental index differs from traditional capitalization-weighted indices in several important aspects. First, the market capitalization is unique in the sense that it is the only portfolio which every investor can hold.[7] Fundamental indices, on the other hand, cannot be held in equilibrium by every investor.[8] For every stock that is overweighted by fundamental investors there must, by definition, be some other investor who actively underweights the same stock, and vice verse. Thus, for fundamental investors to outperform against a capitalization-weighted index, there must be some other group of

[7] For a vivid discussion of this point, see Asness (2006).
[8] Except of course for the trivial case in which the two happen to be exactly the same.

investors with opposing views who underperform, and vice verse. However, it is not immediately clear which investor characteristics determine that it is optimal to be a fundamental indexer or not. The proponents of fundamental indexation also fail to explain why, in equilibrium, a certain group of investors would want to invest in fundamentally unattractive stocks.

Second, contrary to a market capitalization-weighted index, a fundamental index does not represent a passive, buy-and-hold strategy. Mirroring a cap-weight index requires no turnover, except in case of index changes due to new share issuance. A fundamental index, on the other hand, requires some kind of rebalancing strategy, as changes in stock prices continuously push weights away from their fundamental target levels. In the absence of transaction costs, the ideal fundamental index would be rebalanced continuously. Note, however, that a continuously rebalanced fundamental index will exhibit a negative exposure towards momentum compared to a capitalization-weighted index, as it continuously needs to sell stocks that have done well (so for which the weight has increased) and buy stocks that have done poorly (so for which the weight has decreased). This may explain why fundamental index providers propose low rebalancing frequencies, which make their indices deviate more from the theoretical ideal. In addition to saving on transaction costs, this prevents the fundamental indices from getting a large negative exposure to the momentum effect, which historically would have hurt their performance.[9]

Third, several subjective choices need to be made in order to define a fundamental index. Most notably, which particular fundamentals are considered in the construction of the index (e.g. book value, sales, earnings, cash-flow, dividends, etc.) and how exactly should these be defined to construct the index. Also, relating to our previous point, a rebalancing strategy needs to be defined.[10]

In sum, it is not clear who holds the fundamental indexing portfolio in equilibrium, fundamental indexation does not represent a buy-and-hold strategy and fundamental indexation requires subjective choices. These characteristics of fundamental indices actually bear more resemblance with an active investment strategy than with traditional passive indices. Based on these observations we conclude that fundamental indexation is essentially an active value strategy disguised as an index.

[9] The RAFI 1000 still has a slightly negative exposure to the momentum strategy from Fama's website.
[10] Blitz, van der Grient and van Vliet (2010) show that subjective rebalancing assumptions can have a large impact on the calendar year returns of a fundamental index.

4.4 Fundamental indexation is a sub-optimal quantitative strategy

In the previous sections we concluded that fundamental indexing is simply a way to gain exposure to the well-known value premium. Although this is not something unique, it might still be a useful idea in practice. For example, there could remain a case for fundamental indexation if it is a highly efficient way of capturing the value premium. However, fundamental indexation is in fact more likely to be a sub-optimal way of benefiting from the value premium. This is because fundamental indices are primarily designed for simplicity and appeal, and not for optimal risk/return characteristics, as measured by the Sharpe ratio or information ratio for example. Arnott et al (2005) report a Sharpe ratio improvement from 0.301 to 0.444, and an associated information ratio of 0.47 for fundamental indexation.[11] Although these figures are not bad, they are also not spectacular. Furthermore, the outperformance is not very consistent over time, as it tends to be concentrated in certain periods (such as the post 2000 period), while even being negative during others (such as the nineties). Quantitative value strategies which are specifically designed for optimal risk/return characteristics should therefore be able to beat fundamental indexation strategies, not just historically but also in the future.

Furthermore, it is important to realize that fundamental indexation is solely trying to benefit from the value premium, which happens to be just one particular well-known empirical return irregularity. Multi-factor quantitative investment strategies allow investors to benefit from many more anomalies which have been documented empirically, such as for example the medium-term price momentum effect (Jegadeesh and Titman 1993), the short-term reversal effect (Jegadeesh 1990), the earnings momentum effect (Chan, Jegadeesh , and Lakonishok 1996) , the accruals effect (Sloan 1996) and the low volatility effect (Blitz and Van Vliet 2007). Not surprisingly, multi-factor quantitative investment strategies are able to generate significantly better results (typically information ratios well above 1) over the same period as studied by Arnott et al (2005). These anomalies together could in similar spirit to a fundamental index be captured in a “behavioral finance index” that could be tracked by passive managers or serve as a benchmark for (quantitative) active portfolio managers.

We conclude that although fundamental indices may appear to be an appealing alternative to traditional market capitalization weighted indices, their risk-return characteristics are dominated by more sophisticated quantitative strategies which allow for

[11] This information ratio was derived by taking the reported outperformance of 2.15% and dividing this by the associated tracking error of 4.57%.

more flexibility with regard to exploiting the value effect, and which are able to benefit from other return irregularities as well.

4.5 Conclusion

In this paper we have examined the added value of the appealing new concept of fundamental indexation. First we have argued that because the weight differences between a fundamental index and a market capitalization-weighted index are entirely due to differences in valuation ratios, i.e. fundamental values compared to market capitalizations, fundamental indices are by definition nothing more than a new breed of value indices. Next we have argued that fundamental indices more resemble active investment strategies than classic passive indices, because (i) they appear to be inconsistent with market equilibrium, (ii) they do not represent a buy-and-hold strategy and (ii) they require several subjective choices. Because fundamental indices are primarily designed for simplicity and appeal, they are unlikely to be the most efficient way of benefiting from the value premium. The risk/return characteristics of fundamental indices are likely to be even more inferior compared to more sophisticated quantitative strategies, which also try to exploit other anomalies in addition to the value effect.

5 Global Tactical Cross-Asset Allocation[1]

5.1 Introduction

The objective of Global Tactical Asset Allocation (GTAA) is to improve on a given strategic asset allocation by tactically adjusting the weights of asset classes based on their perceived attractiveness. A popular approach to GTAA is to first develop various complementary allocation models, each with a limited scope, that can subsequently be used as building blocks for a comprehensive GTAA strategy.[2] For example, one could start with an equity market timing model, and then add a bond market timing model, global country allocation models (both for equities and bonds) and finally a currency allocation model. The next stage entails assigning appropriate risk budgets to each of these models in order to obtain the actual GTAA strategy. For a discussion of a comprehensive GTAA risk budgeting framework, see Sharpe (1987) and Lee (2000). Existing literature provides many useful leads for developing GTAA building-block models. For example, Fama and French (1989) show that factors such as the term spread and dividend yield contain predictive power for the future equity risk premium. The term spread has also been related to future bond returns, for example by Fama and Bliss (1987) and Ilmanen (1995). For equity country allocation both medium term momentum and long-term mean-reversion have been shown to be effective, see Chan et al. (2000) and Richards (1995, 1997). As a final example we mention carry strategies for currencies, as documented by Hodrick (1987) and Froot and Thaler (1990).

The traditional approach outlined above simplifies the GTAA problem by breaking it down into several smaller problems, which can be handled separately. Each building-block model considers a limited number of similar assets, and can take into account the specific variables that are considered to be relevant for that particular allocation decision. However, by not directly comparing each asset to every other asset in the opportunity set, the full potential of GTAA may be left unrealized. Another drawback of the multi-model approach is that it takes a considerable amount of effort to develop the separate building-block models, which is why in practice often only a limited number of

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[1] This chapter is based on Blitz and van Vliet (2008). The authors thank Thierry Post, Laurens Swinkels and an anonymous referee for valuable comments on an earlier version of this paper and Xiaomin Pang for research assistance.

[2] Goldman Sachs is an example of a well-known GTAA provider using this approach, see for example http://www2.goldmansachs.com/client_services/asset_management/institutional/pdf/global_tactical.pdf.

models are actually employed in GTAA strategies. Furthermore, combining the positions indicated by the different models requires a sophisticated risk budgeting approach for managing aggregate portfolio risk. These issues are addressed by the alternative approach to GTAA presented in this paper, which is characterized by the use of a single model to directly compare the attractiveness of a broad and diverse range of asset classes. We call this approach Global Tactical Cross-Asset Allocation, or GTCAA.

The key question which we address is if classic cross-sectional return patterns, which have previously been documented at the security level, can also be observed across asset classes. This topic has received surprisingly little attention in the existing literature. Clearly, if the cross-section of asset class returns cannot be explained by the current set of pricing models, then this would add yet another puzzle to the field of empirical asset pricing. Given that a cross-asset allocation strategy can be implemented relatively easily using a limited number of highly liquid instruments such as futures, finding a profitable GTCAA strategy would pose a formidable challenge to market efficiency.

Using US stock data, Jegadeesh and Titman (1993) document a strong 6-month return momentum effect. Fama and French (1996) show that many US stock market effects can be explained by exposure to the size and value premiums, with the exception of 12-1 month momentum. Fama and French (1998) and Rouwenhorst (1998) also document value and momentum premiums for international stock markets. Pirron (2005), one of the few papers which takes a cross-market perspective, reports significant profits for 3 to 12 month price momentum strategies applied to futures markets. Interestingly, mixed results have been found for portfolios based on past 1-month returns. Jegadeesh (1990) finds a short-term reversal effect at the stock level, while Moskowitz and Grinblatt (1999) find a short-term momentum effect at the industry level.

In this paper we examine value and momentum strategies for tactical allocation across a broad range of asset classes.[3] Applying price momentum to cross-asset allocation is relatively simple, as this strategy only requires past returns as input. We will consider both a 12-1 month momentum strategy and a strategy based on 1-month returns. Constructing a cross-asset allocation value strategy is less straightforward, as there is no obvious valuation measure which is applicable to every asset class. The essence of our valuation strategy is to compare asset classes using relatively simple yield measures. We describe our approach in detail in the methodology section.

[3] We did not attempt to test for a GTCAA size effect. A priori we do not expect to find a size effect across asset classes, as the size of an asset class is not a straight reflection of the economic size of the underlying securities, but also depends on the breadth of that asset class, i.e. the number of different securities.

Our main finding is that the application of momentum and value strategies to global tactical asset allocation across twelve asset classes delivers statistically and economically significant abnormal returns. We document return premiums between 7-8% for the 1-month momentum, 12-1 month momentum and value GTCAA strategies over the 1986-2007 period. Interestingly, the 1-month momentum effect is in line with previous findings at the industry level, and contrary to the reversal effects which are reported at the stock level. For a GTCAA strategy based on a simple combination of momentum and value factors we find an alpha of 12% per annum. Performance is stable over time, also present for a reduced set of assets over the 1974-1985 period, and sufficiently high to overcome transaction costs in practice. Furthermore, the performance is robust to adjustments for implicit market exposures and is also largely unaffected by adjustments for implicit loadings on the CAPM market factor, the Fama-French size and value factors and the Carhart momentum factor.

Our findings are relevant for both theoretical and practical reasons. From a theoretical perspective our findings may challenge market efficiency and market equilibrium. Furthermore, our results imply that value and momentum effects are not only present within specific asset classes, but also transcend across entire asset classes. Although there is in fact no generally accepted asset-pricing model which applies to the wide variety of asset classes which we consider in this paper, we argue that any such model is unlikely to be able to explain the return effects which we find in our analysis. Interestingly, the momentum and value effects which we observe across different asset classes are similar in magnitude, but at most partly related to the momentum and value effects that have previously been documented within asset classes and for which behavioral explanations have been put forward. Inspired by these, we also provide a possible behavioral explanation for the momentum and value effects which we observe across asset classes.

For practitioners our results are interesting because they provide a single-model approach to GTAA, which may be used as either an alternative to multi-model GTAA strategies, or as an additional building block for such strategies. One of the limitations of our cross-asset allocation approach is that it cannot easily incorporate asset-specific variables. For example, analysts' earnings revisions might be a relevant factor for equity markets, but bond markets lack an obvious equivalent measure. Hence, with GTCAA the focus is more on breadth (covering many assets with a limited set of factors) than on depth (covering a single allocation decision with many asset-specific factors).

The remainder of this paper is organized as follows. In the next section we first describe the data and methodology. Next we present our main results for momentum and valuation strategies applied to Global Tactical Cross-Asset Allocation. The subsequent section contains various robustness tests. This is followed by a discussion of possible explanations for our findings. We end with conclusions and implications for investors.

5.2 Data and methodology

Table 5.1 gives an overview of the asset classes that constitute the opportunity set for our analyses and the indices that we use to measure the returns of these asset classes. The total number of asset classes is twelve. Three of these relate to the US equity market, namely US large-cap equities, US mid-cap equities and US real estate equities (REITS). We also include three international equity markets, specifically the UK, Japan and emerging markets. Three US bond asset classes are included, namely US Treasuries, US investment grade bonds and US high yield bonds. In addition we include the two main international bond markets, Germany and Japan. The final asset is a US 1-month LIBOR cash investment, which serves as our proxy for the risk-free alternative.

Although the selection of these asset classes was not based on a formal set of rules, we did take into consideration a number of criteria, in particular for which asset classes not to include:

- asset classes for which less than twenty years of data history is available, e.g. emerging debt and hedge funds;
- asset classes which are more difficult to model, especially with regard to valuation, e.g. commodities and currencies;
- asset classes which are illiquid and/or lack market prices, e.g. direct real estate and private equity; asset classes with a limited market capitalization and/or limited economic relevance, e.g. micro-cap stocks;
- asset classes which are highly correlated and would reduce the heterogeneity of the investment universe, e.g. the inclusion of each of the twenty largest stock markets as separate assets[4]

For each asset class, except emerging markets equities, we take total returns in local currency and subtract the local risk free return, i.e. US, UK, Japan or German 1-month LIBOR. These excess returns resemble the returns that can be obtained in practice with futures contracts, although it should be noted that these are (or were) not actually available

[4] In this way we also avoid that our universe is basically an equity country allocation universe (for which a lot of research is already available) ‘plus a few other assets’.

in practice for all assets.[5] For emerging markets equities we take open (unhedged) returns in US dollars in excess of the US 1-month LIBOR return.

Table 5.1

Indices used

This table gives an overview of the asset classes considered in this study and the indices that are used to measure the performance of these asset classes.

Asset class	Index	Start date
US large-cap equity	S&P 500 (prior to 1988: Datastream calculated)	Jan-70
US mid-cap equity	S&P 400 Datastream calculated	Feb-73
US real estate equity	FTSE/NAREIT	Feb-72
UK equity	FTSE 100 (prior to 1986: MSCI UK)	Jan-70
Japan equity	TOPIX	Feb-73
US Treasury bonds	Lehman US Treasury	Feb-73
US investment grade bonds	Lehman US Corporate investment grade	Feb-73
Cash (risk-free)	1M LIBOR	Jan-70
Emerging markets equity	S&P/IFC Investable Emerging Markets (prior to 1989: S&P/IFC Global Emerging Markets)	Jan-85*
US high yield bonds	Lehman US High Yield (prior to 1987: Merrill Lynch High Yield 175)	Jan-80
German government bonds	Citigroup government bond Germany	Jan-85
Japan government bonds	Citigroup government bond Japan	Jan-85

* Valuation data for emerging markets equity starts in Jan-86

The earliest date for which return data is available for every asset class in our universe is January 1985. Because 12-1 month momentum is among the strategies that we want to analyze, our analysis effectively starts at the end of January 1986. This is actually also the first month for which valuation data is available for every asset class. The last month of our sample period is September 2007. Table 5.2 summarizes the risk and return characteristics of each asset class over the full sample period. Average annual excess

[5] Nowadays, markets are more liquid and more instruments are available than in the earlier part of the sample. For example, besides futures, OTC swaps or ETFs may constitute efficient alternative instruments for efficiently gaining exposure during the latter part of the sample.

returns vary between less than 1% (for Japan equity) and almost 11% (for emerging markets equity). Sharpe ratios for the individual asset classes vary between 0.03 (again for Japan equity) and 0.56 (for US investment grade bonds).

Table 5.2

Asset class risk/return characteristics

This table shows the annualized geometric excess return, standard deviation and Sharpe ratio for our sample of asset classes over the period February 1986 through September 2007.

Asset class	Geometric mean	Standard deviation	Sharpe-ratio
US large-cap equity	6.6%	14.8%	0.45
US mid-cap equity	6.7%	15.6%	0.43
US real estate equity	5.3%	12.9%	0.41
UK equity	3.5%	15.6%	0.22
Japan equity	0.7%	19.6%	0.03
US Treasury bonds	2.1%	4.7%	0.44
US investment grade bonds	2.7%	4.9%	0.56
Cash (risk-free)	0.0%	0.0%	n.a.
Emerging markets equity	10.8%	23.0%	0.47
US high yield bonds	3.4%	7.3%	0.47
German government bonds	1.4%	3.3%	0.43
Japan government bonds	2.2%	4.0%	0.55

At the end of every month we rank all assets based on their momentum and/or valuation scores, and use this ranking to assign the assets to four quartile portfolios consisting of three assets each. We then calculate the return of each quartile portfolio over the following month. In addition to the four long-only quartile portfolios we also consider a long top-quartile and short bottom-quartile zero-investment portfolio. This process is repeated until the end of the sample period. Transaction costs are not included in the initial strategy evaluation, but are discussed separately in a sensitivity analysis.

Our methodology is consistent with classic empirical studies of cross-sectional return patterns at the security level. The fact that our long/short portfolio effectively consists of three pair trades is also conceptually consistent with the theoretical result in Lee (2000), that optimal bet sizes in TAA strategies are directly driven by the pairwise differences in expected returns of assets.[6] Our pair trades may consist of traditional TAA bets, such as long US large-cap equities and short US Treasuries, but they can also be less conventional, such as long US real estate equities and short Japanese government bonds. Instead of a weakness this may actually be a strength of our cross-market approach. In the discussion section we will argue that inefficiencies may arise at the level of asset classes, because many investors perceive full-fledged global tactical asset allocation to be too challenging. We also note that when stand-alone long/short timing strategies are applied to the individual assets within a broadly diversified strategic allocation[7], the net outcome may well consist of some unconventional pair trades.

We will examine both a 1-month return strategy and a classic 12-1 month (12 months excluding the most recent month) momentum strategy. Only return data is required for these analyses. In addition to the two momentum strategies we also consider a cross-asset valuation strategy. This strategy is less straightforward, as it requires valuation data that can be used for making direct cross-sectional comparisons of asset classes. The starting point of our approach is to take a simple yield measure for each asset class. For equity assets we take the (trailing) earnings yield (E/P ratio), while for bond assets we take the standard yield-to-maturity.[8] Both yield measures are adjusted for the appropriate (local) risk-free rate of return, as shown in the third column of Table 5.3. Note that for the bond assets this means that we are effectively taking the term premium as our valuation indicator.

The simplicity of using these basic yield measures is appealing, but it is questionable if sensible comparisons of different asset classes can be made with such an elementary approach. Indeed, it is not difficult to illustrate that this approach is overly simplistic and needs to be refined. Consider for example the yield on US high yield bonds versus that on comparable US Treasury bonds. Obviously, the difference should always be positive, as investors require a compensation for being exposed to default risk. Thus, an adjustment for default risk should be made in order to prevent US high yield bonds from being structurally preferred to US Treasuries. Without such an adjustment, US high yield bonds would in fact end up in the top quartile value portfolio 93%(!) of the time. For other

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[6] By additionally taking into account the covariance matrix of asset returns the full potential of TAA can be unlocked. We partly address this issue in the sensitivity analysis where we use volatility adjusted bet sizes instead of equal bet sizes.

[7] The specific strategic asset allocation of an investor will actually be ignored in our analysis, based on the finding in Lee (2000) that when tactical asset allocation is approached from a portable alpha perspective, the optimal tactical bets are entirely independent of the underlying benchmark portfolio.

[8] As earnings yield data is unfortunately not available for US real estate equities, we decided to use dividend yield data instead for this asset class. This is actually not a bad approximation, as REITS are legally obliged to distribute at least 90% of their income as dividends.

assets the need for an adjustment to the basic yield measure might be less obvious at first sight, but equally necessary. For example, yields on government bonds are not necessarily directly comparable to those on stocks.

Table 5.3

Valuation measures

This table gives an overview of the valuation measures used for the asset classes in our sample and the fixed adjustments that are applied to some asset classes.

Asset class	Valuation measure	LIBOR reference point	Raw average	Extra hurdle	Average with extra hurdle
US large-cap equity	E/P	US 1M	-0.2%	-	-0.2%
US mid-cap equity	E/P	US 1M	0.6%	-	0.6%
US real estate equity	D/P	US 1M	2.5%	2%	0.5%
UK equity	E/P	UK 1M	-1.0%	-	-1.0%
Japan equity	E/P	Japan 1M	-0.2%	-	-0.2%
US Treasury bonds	Yield	US 1M	0.9%	1%	-0.1%
US investment grade bonds	Yield	US 1M	2.2%	2%	0.2%
Cash (risk-free)	1M LIBOR	US 1M	0.0%	-	0.0%
Emerging markets equity	E/P	US 1M	0.9%	1%	-0.1%
US high yield bonds	Yield	US 1M	6.2%	6%	0.2%
German government bonds	Yield	German 1M	0.7%	1%	-0.3%
Japan government bonds	Yield	Japan 1M	0.6%	1%	-0.4%

For our valuation strategy we apply a limited number of asset-specific, fixed adjustments to the basic yield data. These adjustments were chosen in such a way that the main structural biases towards certain asset classes are removed. Specifically:

- for the government bond assets, US Treasuries and German and Japanese government bonds, we subtract 1% from the term premiums, which adjusts for the fact that the yield curve tends to be upward sloping;
- for US investment grade credits we subtract 2% and for US high yield bonds 6%, also to adjust for the slope of the yield curve, and additionally to adjust for default risk;
- for emerging markets equities we subtract 1% to adjust for the structurally lower P/E compared to mature equity markets;
- for US real estate equities we subtract 2% to adjust for the structurally higher yield compared to regular equities.

By comparing the average valuation scores before and after these adjustments, shown in the second-to-last and last columns of Table 5.3, it can be seen that these adjustments result in scores that are much more comparable across asset classes. In fact, after applying the adjustments, the long-term average valuation score for every asset falls in a range between -1% and +1%, which implies that structural biases towards certain asset classes are effectively eliminated.[9]

Given the valuation scores, the valuation investment strategy is tested in a similar way as the momentum strategies discussed earlier, i.e. based on quartile portfolios with a monthly rebalancing frequency. To better understand the interaction between the valuation and momentum effects, we also analyze a combined investment strategy. A combined score for each asset class is calculated by taking a weighted average of its rank (1 to 12) on the individual variables. We choose for a simple 50/50 balance between the momentum and valuation strategies and equal weighting of the two momentum variables. This translates into weights of 25% for 1-month momentum, 25% for 12-1 month momentum and 50% for valuation.[10] The correlation structure between the three underlying strategies, which is discussed in the next section, provides an additional motivation for this choice of weights.

5.3 Results

5.3.1 Main results

The main results of our analysis are presented in Table 5.4. The top (first) quartile portfolios for the 1-month momentum, 12-1 month momentum and valuation strategies can be seen to generate relatively high returns and Sharpe-ratios, while the bottom (fourth) quartile portfolios are associated with the lowest returns and Sharpe ratios. The second and third quartile portfolios tend to fall neatly in between, resulting in a monotonic

[9] The price which we have to pay for obtaining a more reasonable value strategy without structural biases is that our adjustments introduce a look-ahead bias, because in the past an investor might have considered certain alternative adjustment levels to be more appropriate. However, we also find strong results (not reported) for an alternative valuation strategy which is free of look-ahead bias. This approach consists of normalizing the valuation level of an asset class by adjusting for its own historical average. Disadvantages of this alternative approach are that it is more data intensive (as a result of which the sample period is shortened) and the introduction of another kind of ambiguity (which lookback period, different adjustments for similar assets, etc.).

[10] In order to avoid occasional ties we actually give a 25.01% weight to the 12-1 month momentum variable. We choose to give a little bit more weight to the slower momentum factor in order to limit turnover.

performance pattern over the four quartile portfolios. The long top-quartile and short bottom-quartile (Q1-Q4) zero-investment portfolio generates positive annualized returns of 6.9% for 1-month momentum, 7.9% for 12-1 month momentum and 7.9% for valuation, which are all statistically significantly different from zero at the 1% significance level. Interestingly, the 1-month momentum effect is in line with previous findings at the industry level, and contrary to the reversal effects which are reported at the stock level. Furthermore, the GTCAA 12-1 month momentum effect is similar in magnitude to the US stock market momentum effect (UMD, 8.4% during our sample), while the GTCAA value

Table 5.4

Main results

This table shows the main results for value, momentum and combination cross-asset allocation strategies. Returns are in excess of the risk-free rate of return, log-transformed and annualized. The sample period is from February 1986 until September 2007.

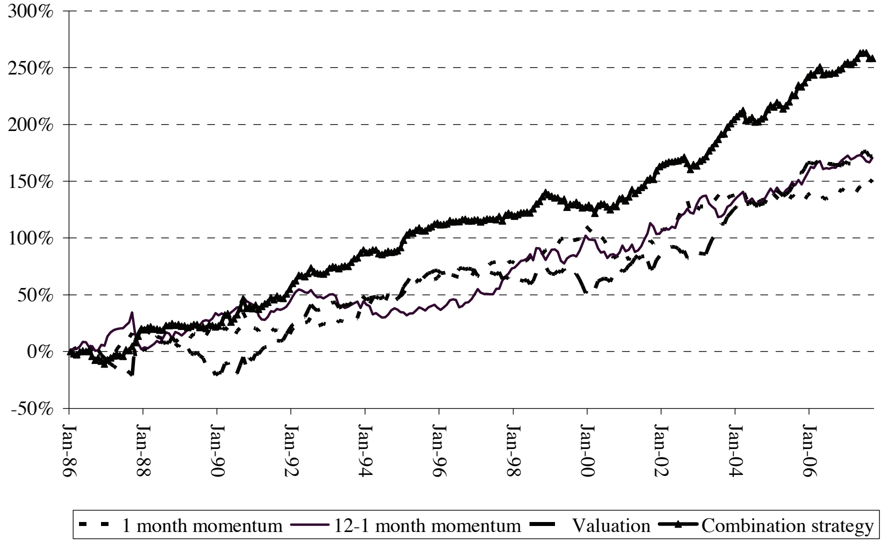
	Q1	Q2	Q3	Q4		Q1-Q4
1 month momentum						
Mean return	9.9%	3.9%	-0.7%	3.0%	Outperformance	6.9%
Standard deviation	10.7%	7.0%	8.0%	11.1%	Tracking error	12.0%
Sharpe-ratio	0.93	0.57	-0.09	0.27	Information ratio	0.57
					T-statistic	(2.67)
12-1 month momentum						
Mean return	8.1%	4.0%	3.9%	0.2%	Outperformance	7.9%
Standard deviation	11.6%	8.1%	6.9%	10.7%	Tracking error	13.0%
Sharpe-ratio	0.70	0.49	0.56	0.02	Information ratio	0.61
					T-statistic	(2.82)
Valuation						
Mean return	8.9%	3.3%	3.0%	1.0%	Outperformance	7.9%
Standard deviation	9.1%	7.7%	7.9%	12.5%	Tracking error	13.2%
Sharpe-ratio	0.98	0.42	0.37	0.08	Information ratio	0.60
					T-statistic	(2.79)
Combination strategy						
Mean return	10.4%	6.2%	1.4%	-1.6%	Outperformance	11.9%
Standard deviation	8.7%	7.6%	9.4%	9.9%	Tracking error	10.0%
Sharpe-ratio	1.19	0.81	0.14	-0.16	Information ratio	1.19
					T-statistic	(5.56)

effect is even larger than the value effect within the US stock market (HML, 3.4% during our sample). We conclude that all three variables exhibit significant predictive power for Global Tactical Cross-Asset Allocation purposes.

Figure 5.1

Cumulative return Q1-Q4 strategies

This figure shows the cumulative return of top-minus-bottom quartile cross-asset allocation strategies based on 1-month momentum, 12-1 month momentum, valuation or a combination strategy.



The two momentum strategies exhibit a positive correlation of 0.3 with each other, and negative correlations of -0.1 to -0.3 with the valuation strategy. These relatively low correlations indicate that we are capturing three distinct effects. The correlation structure also provides an additional motivation for our choice of weights in the combined strategy, as it makes sense to reduce the weight of variables that are positively correlated (the two momentum variables) and increase the weight of variables that exhibit negative correlations (valuation). Given the relatively low correlations it is not surprising that the performance of the combined strategy is superior to each of the underlying strategies. The top-quartile portfolio for the combined strategy outperforms the top-quartile portfolios of the underlying strategies, and for the bottom-quartile portfolio of the combined strategy we find the lowest returns so far. This results in a return of 11.9% per annum for the long/short combined strategy, which is highly significant with a t-statistic of well over 5.

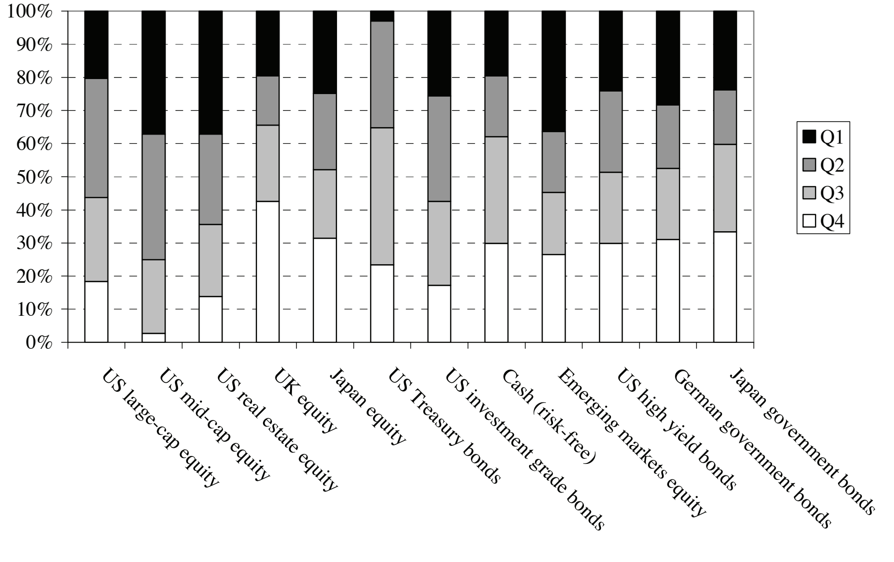
The volatility of the strategy is 10%, somewhere between equity and bonds, which results in an information ratio of 1.2. Figure 5.1 shows the cumulative returns for both the combined and the individual strategies over time. Performance can be seen to be quite stable over time, and is, for example, not just concentrated in the early years of the sample.

Next we examine if perhaps the returns of the strategies might be explained by structural biases towards certain asset classes. If we consider for example a naïve portfolio which goes systematically long in equities and short in cash, then the return which is captured by this portfolio simply reflects the equity risk premium. Thus, our concern is that the quartile portfolios may have structurally different exposures to the risk premiums that are offered by the various asset classes. The importance of adjusting for such structural biases is also stressed by Lee (2000). For the combined strategy we therefore look at the frequency with which each asset class is selected for each of the quartile portfolios. In Figure 5.2 it can be seen that the asset class which is selected most frequently in the top-quartile portfolio is US real estate equities (REITS), while UK equities tend to be the least favorite asset class. We also observe that each asset class occurs in each of the quartile

Figure 5.2

Average distribution across quartile portfolios for each asset class

This figure shows the frequency with which each asset class is selected for each of the quartile portfolios for the combination strategy.



portfolios for at least 3% of the observations, and no asset class occurs in any quartile portfolio for more than 43% of the time.[11] This indicates that the combined value-momentum GTCAA strategy does not have a large structural bias towards one specific asset class.

More formally, we calculated for each portfolio its average net exposure to each of the twelve asset classes, i.e. measured ex-post over the entire sample period. Using these weights we can create static reference portfolios which, by definition, exhibit the same average exposures to the various asset classes as the original portfolios. By subtracting the returns of these reference portfolios from the returns of the original portfolios, we thus effectively adjust the latter for possible systematic biases towards certain asset classes. The Q1-Q4 return of the combination strategy remains at 11%, again with a highly significant t-statistic larger than 5. Thus, we can conclude that the results are generally robust to the adjustments for implicit systematic biases towards certain asset classes.

In Table 5.5 we adjust the (raw) GTCAA strategy returns for their implicit loadings on the classic CAPM market factor, the Fama French size and value factors and the Carhart momentum factor.[12] These regressions allow us to determine if the GTCAA momentum and valuation returns are unique effects, or simply a cross-asset manifestation of effects that are already known to exist within the US stock market. Table 5.5 shows that a CAPM adjustment does not materially affect the returns of the strategies. The value strategy has a negative loading on the CAPM market factor, while the 12-1 month momentum strategy has a positive beta with regard to the market factor, but these exposures do not subsume their returns. The alphas also remain strong when the Fama French 3-factor adjustment is applied. An interesting observation is that the GTCAA valuation strategy appears to be weakly related to the Fama French value (HML) and size (SMB) factors. The loading on HML suggests that the GTCAA value effect is, to a limited degree, related to the classic value effect within the US stock market. Apparently this relationship is not very dominant though, as the alpha of the GTCAA valuation strategy only drops by about 1%. The same observations apply to the GTCAA combination strategy.

The Fama French / Carhart 4-factor adjustments reveal that the 12-1 month momentum strategy is strongly related to the 12-1 month stock momentum factor (UMD). The GTCAA 12-1 month momentum alpha is in fact subsumed to a large degree and becomes insignificant after adjusting for the UMD momentum factor. Thus, the 12-1 momentum GTCAA strategy is picking up a cross-asset allocation momentum effect which

[11] The same is actually true for each of the three underlying strategies.
[12] The data for this analysis was taken from the Kenneth French website.

Table 5.5

Alphas of the cross-asset allocation strategies

This table shows the alphas based on CAPM, Fama French 3-factor model and Fama French / Carhart 4-factor model adjustments for top-minus-bottom quartile portfolio cross-asset allocation strategies. T-statistics are reported between brackets.

	Alpha	Rm	SMB	HML	UMD
1 month momentum					
CAPM	6.9%	0.00			
	(2.65)	(-0.05)			
Fama French 3-factor model	6.8%	-0.02	0.16	0.03	
	(2.57)	(-0.28)	(2.31)	(0.41)	
Fama French / Carhart 4-factor model	6.3%	-0.01	0.15	0.04	0.04
	(2.33)	(-0.15)	(2.23)	(0.50)	(0.89)
12-1 month momentum					
CAPM	6.9%	0.12			
	(2.48)	(2.21)			
Fama French 3-factor model	6.5%	0.13	0.11	0.08	
	(2.28)	(2.10)	(1.50)	(0.86)	
Fama French / Carhart 4-factor model	1.9%	0.19	0.06	0.15	0.41
	(0.75)	(3.59)	(0.94)	(1.87)	(8.64)
Valuation					
CAPM	9.6%	-0.21			
	(3.43)	(-3.91)			
Fama French 3-factor model	8.5%	-0.17	0.14	0.18	
	(2.99)	(-2.78)	(1.94)	(2.00)	
Fama French / Carhart 4-factor model	11.3%	-0.21	0.17	0.14	-0.25
	(4.04)	(-3.55)	(2.44)	(1.57)	(-4.81)
Combination strategy					
CAPM	12.4%	-0.07			
	(5.76)	(-1.60)			
Fama French 3-factor model	11.0%	-0.01	0.17	0.23	
	(5.12)	(-0.25)	(3.03)	(3.38)	
Fama French / Carhart 4-factor model	11.0%	-0.01	0.17	0.23	0.00
	(4.98)	(-0.24)	(3.00)	(3.36)	(0.08)

is closely related to the well-known momentum effect within the US stock market.[13] As both UMD and the cross-market 12-1 month momentum strategy earn premiums of 8% during our sample period, one could also argue that UMD can be mimicked with our cross-market 12-1 month momentum strategy. This is an interesting observation, because the UMD momentum premium is difficult to capture in reality, as it involves frequent trading in many hundreds of individual stocks. Our cross-market strategy, on the other hand, involves only twelve highly liquid asset classes and is thus a much easier strategy in practice. The GTCAA 1-month momentum strategy is not affected by a UMD correction.

Interestingly, the GTCAA valuation strategy exhibits a strong negative loading on the momentum factor, which strengthens its 4-factor alpha. For the GTCAA combined strategy these effects turn out to offset each other, as in this case the effective exposure to the momentum factor is insignificant. As a result, the alpha of the GTCAA combined strategy is robust to CAPM, 3-factor and 4-factor model adjustments and remains very strong at 11-12% per annum.

5.3.2 Robustness tests

In this section we further examine the robustness of our findings. First we analyze the impact of transaction costs. For this we begin by calculating the amount of turnover that is associated with the Q1-Q4 strategies. The maximum annual (monthly) turnover is 2400% (200%) one-way, in the event that all long and short positions would be replaced every month.[14] Table 5.6 shows that the annual turnover varies from about 200% for the valuation strategy to 1600% for the 1-month momentum strategy. In order to translate the turnover figures into an estimate of annual transaction costs, we need to assume a certain level of transaction costs for individual trades. Instead of choosing one particular level of transaction costs per trade we will consider three different levels: 10 bp, 25 bp or, most conservatively, 50 bp. The 10 bp figure represents a realistic estimate in case the strategies could be implemented using highly liquid instruments such as futures. As this assumption

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[13] This finding differs from the cross-market momentum results of Pirrong (2005), who also performed a four-factor correction which did not significantly affect the alpha. This might be attributed to differences in the universe of assets and/or sample period.

[14] In practice transaction costs might be reduced significantly by applying more advanced buy and sell rules. For example, an asset which drops from rank three (out of twelve) to four falls out of the top quartile and is thus replaced in the Q1-Q4 portfolio. However, given the fact that the change in ranking is only one notch and given that the second-quartile portfolio also outperforms, it may in fact be more attractive to hold on to the position in such an asset on an after-cost basis.

may be too optimistic, especially historically, we also consider the more conservative transaction cost levels.

Table 5.6

Turnover

This table shows the annualized turnover (one-way) and returns after transaction costs for top-minus-bottom quartile portfolio cross-asset allocation strategies.

	Turnover	Performance after transaction costs @			
		-	0.10%	0.25%	0.50%
1 month momentum	1675%	6.9%	3.5%	-1.5%	-9.9%
12-1 month momentum	491%	7.9%	6.9%	5.4%	3.0%
Valuation	234%	7.9%	7.5%	6.8%	5.6%
Combination strategy	728%	11.9%	10.5%	8.3%	4.6%

Table 5.6 shows estimated returns after transaction costs for the Q1-Q4 strategies. Comparing these to the results before costs in Table 5.4 it is clear that transaction costs are critical for the high turnover 1-month momentum strategy. At a cost level of 10 bp about half the performance of this strategy is lost, while performance is completely wiped out if costs are assumed to be more than 20bp per trade. Not surprisingly, the slower 12-1 month momentum and valuation strategies are less sensitive to transaction costs. For example, at costs of 25 bp per trade, a third of the performance of the 12-1 month momentum strategy is lost and only about 15% of the performance of the valuation strategy. The combined strategy is well able to survive a realistic level of transaction costs, as even with transaction costs of 50 bp per trade an outperformance of 5% per annum remains. We also note that it is likely that the return can be improved significantly in practice by considering more sophisticated buy/sell rules, or a portfolio optimization which (a.o.) is able to trade off gross expected returns against the transaction costs associated with trading. These extensions are beyond the scope of this paper however. We conclude that a GTCAA strategy can generate sufficient performance to overcome the transaction costs that would be incurred in a real-world implementation.

A second robustness test is a pre-sample test on the period from January 1974 to January 1986. Unfortunately data for the last four asset classes in Table 5.1, emerging markets equities, US high yield bonds, German government bonds and Japanese government bonds, are not available over this period. As a result, the number of asset classes drops to eight, and each quartile portfolio consists of only two instead of three asset classes. Table 5.7, which is similar in structure to Table 5.4, shows that the returns of the various GTCAA strategies tend to be somewhat lower, but still strong over this out-of-sample period.

Table 5.7

Out of sample test

This table shows the results of an out-of-sample test of our cross-asset allocation strategies on a reduced set of 8 asset classes over the period from January 1974 until January 1986. Returns are in excess of the risk-free rate of return, log-transformed and annualized.

	Q1	Q2	Q3	Q4		Q1-Q4
1 month momentum						
Mean return	4.7%	5.3%	-0.6%	0.8%	Outperformance	3.9%
Standard deviation	13.7%	10.2%	11.9%	14.6%	Tracking error	13.4%
Sharpe-ratio	0.35	0.51	-0.05	0.06	Information ratio	0.29
					T-statistic	(1.01)
12-1 month momentum						
Mean return	2.7%	4.3%	5.2%	-2.2%	Outperformance	5.0%
Standard deviation	12.2%	11.3%	11.2%	17.3%	Tracking error	18.7%
Sharpe-ratio	0.23	0.38	0.47	-0.13	Information ratio	0.27
					T-statistic	(0.92)
Valuation						
Mean return	9.1%	3.5%	-4.8%	2.5%	Outperformance	6.6%
Standard deviation	15.3%	13.2%	9.8%	11.9%	Tracking error	14.4%
Sharpe-ratio	0.60	0.26	-0.49	0.21	Information ratio	0.46
					T-statistic	(1.60)
Combination strategy						
Mean return	8.0%	4.1%	-1.0%	-0.7%	Outperformance	8.8%
Standard deviation	13.2%	13.2%	10.5%	12.7%	Tracking error	12.7%
Sharpe-ratio	0.61	0.31	-0.10	-0.06	Information ratio	0.69
					T-statistic	(2.40)

In a third robustness test we look at the effects of using asset class returns that are adjusted for their volatility. Obviously, some assets exhibit much more volatility than others. As a result, the returns of equally weighted portfolios of assets could be dominated by the positions taken in the most volatile assets, such as emerging markets equities. The most volatile assets are also most likely to be either most attractive or least attractive on a measure such as momentum, as these assets tend to produce the most extreme returns. In order to avoid these effects we apply asset-specific volatility adjustments which are intended to make the asset classes more comparable.[15] Specifically, at the end of every month we take for each asset its annualized volatility over the past 60 months, and use this

Table 5.8

Results using volatility-adjusted returns

This table shows the results of cross-asset allocation strategies based on asset-class returns adjusted for their own volatility. Returns are in excess of the risk-free rate of return, log-transformed and annualized. The sample period is from February 1986 until September 2007.

	Q1	Q2	Q3	Q4		Q1-Q4
1 month momentum						
Mean return	7.3%	6.4%	2.1%	-0.1%	Outperformance	7.4%
Standard deviation	7.5%	7.1%	6.1%	8.0%	Tracking error	9.1%
Sharpe-ratio	0.98	0.89	0.34	-0.01	Information ratio	0.82
					T-statistic	(3.79)
12-1 month momentum						
Mean return	5.6%	5.7%	3.6%	0.7%	Outperformance	5.0%
Standard deviation	8.4%	6.1%	6.6%	7.5%	Tracking error	9.6%
Sharpe-ratio	0.67	0.94	0.54	0.09	Information ratio	0.52
					T-statistic	(2.40)
Valuation						
Mean return	6.6%	4.2%	2.5%	2.3%	Outperformance	4.4%
Standard deviation	7.3%	6.2%	7.0%	8.3%	Tracking error	9.5%
Sharpe-ratio	0.92	0.68	0.36	0.27	Information ratio	0.46
					T-statistic	(2.15)
Combination strategy						
Mean return	8.4%	4.8%	3.2%	-0.8%	Outperformance	9.2%
Standard deviation	6.5%	7.4%	7.3%	7.1%	Tracking error	7.8%
Sharpe-ratio	1.29	0.65	0.43	-0.11	Information ratio	1.18
					T-statistic	(5.50)

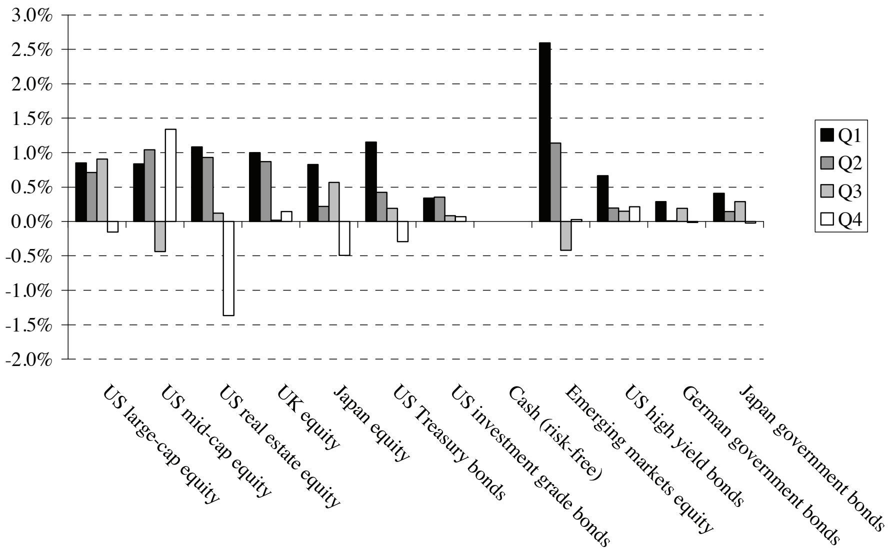
[15] Except the risk-free asset, because this has zero volatility.

to lever or de-lever the position in that asset over the next month to an (arbitrary) target volatility level of 10%.[16] For example, if the trailing volatility of emerging markets equities is 20%, versus only 5% for US Treasuries, we take half the regular position in emerging markets equities and double the regular position in US Treasuries. Table 5.8 shows that the results for this approach remain strong. The Q1-Q4 return for the momentum and valuation strategies on a stand-alone basis is in the 4-7% range, while for the combined strategy it is about 9%. Although at first sight this appears to be lower than for the original strategy, the volatility that is associated with the alternative approach is somewhat lower as well. As a result, both approaches exhibit the same information ratio of 1.2. Thus, the results are clearly robust to the methodological choice of whether or not it is appropriate to adjust asset returns for their volatility.

Figure 5.3

Asset class returns conditional on quintile classification

This table shows for each asset class the average monthly excess return conditional on its quintile classification in the combined strategy.



[16] Note that for some asset classes there is insufficient return history for the initial years of the sample. In such cases we use volatilities calculated over the first 60 months of the series instead. This introduces a slight look-ahead bias, but in our view not a serious one as volatility is used only as a scaling factor.

A final concern which we address is whether the return of the cross-asset allocation strategies might be driven by just one or only a few asset classes. However, the strategy also passes this robustness test without problems. Figure 5.3 shows for each asset class the average monthly return conditional on its quintile classification in the combined strategy. It can be seen that most asset classes earn an average excess return of at *least* 0.3% during the months that they are top ranked, with a median of 0.8% across the different asset classes. During the months of being bottom ranked every asset class, with the only exception of US mid-cap equities[17], earns an average excess return of at *most* 0.2%, with a median of zero. Based on these results we can conclude that the valuation and momentum effects are driven by all asset classes and clearly not by only one or a few.

5.4 Discussion

We continue by discussing possible explanations for our empirical finding that simple momentum and valuation strategies seem highly effective for Global Tactical Asset Allocation across asset classes. It might be that our findings are simply the result of chance or overenthusiastic data mining. In that case the relationships which we have documented would most likely break down in the future, and the alpha opportunity would turn out to be an illusion. Although impossible to rule out we do not consider this explanation to be likely, because the strategies analyzed in this paper are very basic by design and at the same time the statistical significance of the results is quite strong.

Another explanation for our findings might be that we are capturing time-varying risk premiums on the different asset classes and/or that we are not properly adjusting the strategy returns for risk. For example, suppose each asset class can be in either a state of high expected return combined with high risk, or in a state of low expected return and low risk. A strategy which implicitly goes long in assets that tend to be in the high risk state and short assets that tend to be in the low risk state might then seem to be capturing alpha, while in fact the returns that are being generated simply represent a fair compensation for risk. Again we cannot rule out this explanation, but we argue that it also seems unlikely. We begin by noting that the degree of time-variation in risk of the asset classes would have to be quite large in order to justify a return spread of 12% per annum which we found for the combined strategy. The results are in fact so strong that for the bottom-quartile portfolios we find long-term excess returns that are close to zero or even negative, whilst

[17] Further analysis reveals that 12-1 month momentum is the main culprit for the weak performance of the strategy on US mid-cap equity.

even time-varying risk premiums ought to remain positive at all times. Furthermore, there is no evidence of increased risk for the high-return top-quartile portfolio of assets compared to the low-return bottom-quartile portfolio, in terms of volatility, skewness and other measures (statistics not reported).

Table 5.9

Returns in different regimes

This table shows the returns for top-minus-bottom quartile portfolio cross-asset allocation strategies in different regimes. Returns are in excess of the risk-free rate of return, log-transformed and annualized. The sample period is from February 1986 until September 2007.

	VIX		Term spread		Credit spread		Interest rate	
	low	high	low	high	low	high	low	high
1-month momentum	8.9%	6.0%	5.2%	8.2%	6.8%	6.8%	9.1%	4.7%
12-1 month momentum	9.8%	7.1%	6.6%	8.6%	9.6%	6.3%	7.1%	9.4%
Valuation	9.0%	7.2%	6.1%	9.8%	1.1%	12.4%	14.2%	3.5%
Combination strategy	13.9%	10.8%	10.7%	12.9%	9.8%	13.4%	15.7%	8.9%

In Table 5.9 we look at the return of the GTCAA strategies conditional on different macro-economic regimes. For this analysis we used the VIX level, term spread, credit spread and interest rate level as regime indicators.[18] The results are not consistent with a time-varying risk explanation of our results, as alpha spreads are positive in all states-of-the-world. For example, the valuation premium does not depend on VIX or term spread, although it does seem to be higher during periods with low interest rates and low credit spreads, such as for example during the 2003-2006 period. Both our momentum strategies also show no clear link to economic states-of-the-world. For the combined strategy we also do not find an obvious relation between the economic environment on the one hand and the returns of the GTCAA strategy on the other.

If all the explanations that have been put forward above are inadequate, then we are left to consider the possibility that our results may represent a new asset pricing puzzle which challenges market efficiency and market equilibrium. Unfortunately, the concept of market efficiency in the context of GTAA is not well-defined, because there is no

[18] The data are obtained from the St. Louis Federal Reserve. The VIX is the implied volatility on 1-month S&P 100 / 500 index options, the term spread is defined as the difference between 10 year and 1 year US Treasury yields, the credit spread is the difference between Baa and Aaa corporate bond yields and the interest rate level is the 30-day T-bill rate.

generally accepted asset-pricing model which applies to the wide variety of asset classes that are covered in our study. Interestingly, the momentum and value effects which we observe across different asset classes are conceptually similar to the effects that have previously been documented within asset classes or at the level of individual asset-classes and for which behavioral explanations have been put forward. This raises the question as to whether the momentum and value effects which we observe across asset classes might also be capturing inefficiencies caused by behavioral effects and are thus posing a challenge to market efficiency. Inefficiencies at the level of asset-classes might be caused by too little ‘smart money’ being available to actively arbitrage inefficiencies away as soon as they occur. We provide two lines of reasoning which support this hypothesis.

First, many investors may want to refrain from aggressive broad tactical cross-asset allocation simply because they perceive this to be too challenging. As noted earlier, we lack a solid theoretical framework for pricing the heterogeneous set of asset classes covered in our analysis, which means that there is a large degree of uncertainty surrounding the fair valuations of these asset classes. For example, even though empirically we find that our GTCAA valuation strategy is effective, we do not believe that in equilibrium every asset really ought to be valued according to the simple valuation measures which we used in that particular strategy.

Second, most professional market participants such as fund managers and analysts focus on allocation and security selection within a certain asset class. For example, a high yield bond manager tends to focus on picking the best high yield bonds and is usually not particularly concerned about the attractiveness of high yield bonds as an asset class compared to for example REITS. Instead, allocation decisions across asset classes tend to be made primarily by end-investors such as pension fund boards and individuals. Their behavior may be primarily driven by factors such as:

- long-term considerations, e.g. adhering to a strategic mix which follows from an asset-liability management study;
- fixed allocation mechanisms, e.g. the use of a pre-specified asset allocation mix for cash inflows (e.g. 401K plan contributions) throughout a year;
- herding behavior, i.e. not wanting to deviate too much from the peer group;
- recent performance of an asset class, as considerably more money tends to flow into ‘hot’ asset classes which have recently exhibited strong performance than into asset classes with mediocre or disappointing returns.

Following this reasoning it is not hard to imagine that mispricing effects may arise at the level of asset classes. Furthermore, this would also suggest that these effects are likely to persist going forward, at least until more 'smart money' becomes available to actively arbitrage away this opportunity for alpha.

Hedge funds constitute a natural source for this 'smart money', as these funds have the flexibility to take advantage of alpha sources that are ignored by many traditional managers. A priori we would expect managed-futures and global-macro style hedge funds to be particularly likely candidates for engaging in GTCAA type of strategies. In order to investigate whether hedge funds are indeed trying to exploit GTCAA alphas we regress the GTCAA strategy returns on hedge fund returns. The results, shown in Table 5.10, provide a mixed picture.

Table 5.10

Link with hedge funds

This table shows t-statistics of regressions of CSFB/Tremont hedge fund index returns on top-minus-bottom quartile portfolio cross-asset allocation strategies. The sample period is from January 1994 until September 2007. Positive relations that are significant at the 5% level are highlighted in **bold**.

	Multi-factor regression			Single-factor regression
	Mom 1M	Mom 12-1M	Valuation	Combination strategy
Hedge funds	1.2	**2.7**	-2.4	-1.5
Convertible arbitrage	-0.6	0.2	0.0	-0.4
Dedicated short bias	-0.4	-0.6	0.0	-0.7
Distressed	0.7	-0.9	-0.7	0.4
Emerging markets	1.8	-0.6	-2.9	-1.8
Equity market neutral	0.5	-0.4	-1.0	-1.1
Event driven	0.8	-0.7	-0.9	0.1
Event driven multi-strategy	0.7	-0.5	-1.2	-0.4
Fixed income arbitrage	-0.4	1.5	-0.7	-1.4
Global macro	1.6	**2.7**	-2.3	-1.6
Long/short equity	0.5	**3.1**	-2.0	-0.7
Managed futures	**2.2**	**5.4**	1.2	**2.7**
Multi strategy	-0.1	**3.1**	**3.1**	**2.8**
Risk arbitrage	0.2	-1.7	0.6	0.9

On the one hand, we observe that the returns of certain hedge funds do indeed appear to be related to our GTCAA strategies. However, this is mainly driven by exposures to the GTCAA 12-1 month momentum strategy, which we have seen to be strongly related to momentum at the stock level, such as the UMD effect. The GTCAA 1-month momentum and value strategies appear to be considerably less popular among hedge funds, as we find only one positive and significant t-statistic for each of these strategies. For 'global macro', one of our most likely 'smart money' candidates, we even find a significantly negative relation with our GTCAA valuation strategy. Perhaps this is due to the fact that the horizon which is required for this strategy is too long for funds that are strongly focused on short-term performance. More negative exposures are found for other hedge fund styles, and we even find a negative relation between the combined strategy and the aggregate CSFB/Tremont hedge fund index. Thus, we conclude that although some hedge funds may indeed be trying to exploit some of the cross-market allocation alphas documented in this paper, the overall results do not indicate that this is occurring at the large scale which would be needed to arbitrage away all these effects.

5.5 Summary, implications and extensions

We find statistically and economically significant return premiums between 7-8% for 1-month momentum, 12-1 month momentum and value GTCAA strategies over the 1986-2007 period. For a GTCAA strategy based on a simple combination of momentum and value factors we find an alpha of 12% per annum. Our findings are not only relevant for practitioners, but also theoretically, as they show that effects which have previously been documented to exist within asset classes can also be observed across entire asset classes. However, we are not simply capturing known effects in a new way, as the combined strategy returns in particular remain strong after adjusting for implicit loadings on for example the Fama French value and Carhart momentum factors. Thus, although being similar in spirit, the cross-asset effects do in fact constitute different return irregularities. This adds yet another puzzle to the field of empirical asset pricing and a challenge to market efficiency.

We have provided several arguments against risk-based explanations for our findings. Instead, we argue that financial markets may be macro inefficient due to insufficient 'smart money' being available to arbitrage away mispricing effects that may arise due to behavioral effects. Certain types of hedge funds might be expected to represent this 'smart money' and be likely candidates to take advantage of the cross-asset allocation alphas in practice. Although we find some evidence which seems to be consistent with this, other evidence point at behavior which is in fact contrary to our GTCAA strategies.

Our results may be extended in several ways. One direction for follow-up research would be to expand the number of asset classes that is covered by the strategy, for example by adding asset classes for which only a shorter data history is available (e.g. emerging debt, hedge funds), which are more difficult to model (particularly with regard to valuation, e.g. commodities and currencies) or which are less liquid and/or lack market prices (e.g. direct real estate and private equity). A second way of extending the research would be to analyze more potential predictor variables. Variables that are not asset-class specific may be particularly interesting in this regard. For example, Jensen, Mercer and Johnson (1996, 2002) relate monetary conditions to future stock returns and future commodity returns. Calendar and seasonal indicators, such as January or winter/summer effects might be useful as well, or macro-economic indicators, such as consumer and producer confidence, interest rate changes, oil price movements, etc. Thirdly, some form of portfolio optimization might be introduced in order to try to further improve risk-adjusted returns. For example, the simple ranking method used in this paper ignores correlations between the assets that are selected and may thus be suboptimal. By expanding the number of assets, by finding new alpha factors and/or by more advanced portfolio construction the case for Global Tactical-Cross Asset Allocation might be strengthened further.

6 Dynamic Strategic Asset Allocation[1]

6.1 Introduction

The asset allocation decision is known to be very important, determining about 80-90% of return variance, see for example Brinson, Singer and Beebower (1991) and Ibbotson and Kaplan (2000) and Statman (2001) for a discussion of these findings. Realizing this, investors carefully determine an appropriate long-term strategic asset allocation (SAA) policy, e.g. by engaging in an asset liability management (ALM) study. In practice, strategic asset allocation often turns into *static* asset allocation, with a fixed allocation to different asset classes. Although it is known that the risk and return properties of asset classes may vary over the business cycle[2], it is common practice to assume constant risk/return parameters for SAA purposes[3], resulting in one portfolio with constant weights. But although the resulting SAA portfolio is static in terms of composition, its risk and return characteristics may actually exhibit significant time variation over the cycle.

A popular way to exploit time variation in returns is to apply a tactical asset allocation (TAA) overlay on the portfolio, as described by for example Dahlquist and Harvey (2001). However, as the objective of a TAA program is usually to maximize returns within a certain stand-alone risk budget, e.g. a tracking error or value-at-risk limit, it does not offer a solution to time-varying overall portfolio risk. A TAA strategy may in fact turn out to exacerbate the tendency of the SAA portfolio to become more risky during 'bad' economic times, which is particularly undesirable for a risk-averse investor. As Cochrane (1999) points out, a risk-averse investor may prefer a portfolio with a lower Sharpe ratio in a world with time-varying risk and return, in case it offers protection during times of financial distress. Another approach is to use a regime switching (RS) framework

[1] This chapter is based on Blitz and van Vliet (2010). We appreciate the suggestions made by Roy Hoevenaars, Angelien Kemna, Laurens Swinkels, Artino Janssen, Jan Sytze Mosselaar, Jaap van Dam, an anonymous referee, seminar participants at the June 2009 State Street European Quantitative Forum and participants of the Robeco SAA seminar in November 2009.

[2] For example, Sa-Aadu, Shilling and Tiwari (2006) examine diversification benefits of alternative assets across regimes and find that commodities and real estate offer a hedge during periods with low per capita consumption growth (economic bad times). Gorton and Rouwenhorst (2006) find that the diversification benefits of commodities in a balanced portfolio vary across the different phases in the business cycle.

[3] For example, for strategic asset allocation purposes Hoevenaars, Molenaar and Schotman (2007) and Bekkers, Doeswijk and Lam (2009) suggest using long-term historical data for estimating volatilities and correlations, while deriving expected returns from a combination of long-term historical data, economic theory and current market circumstances.

as in Ang and Bekaert (2002, 2004).[4] This approach is based on statistical properties of the underlying assets and typically used to identify two regimes[5]. Ang and Bekaert (2004) argue that the economic mechanism behind their regimes is likely the world business cycle. The main drawback of the regime switching approach is its complexity, as a result of which investment professionals may be reluctant to rely on these models for real-life decision making.[6]

In this paper we propose a simple and transparent framework for dynamic strategic asset allocation (DSAA) based on the business cycle. Contrary to a traditional TAA strategy, this DSAA framework aims at enhancing portfolio return whilst, at the same time, stabilizing portfolio risk across the business cycle. And contrary to more complex regime switching models, which derive regimes from the return characteristics of the assets themselves, our approach uses economic data to model the business cycle directly. By focusing on economic fundamentals, the DSAA framework is designed to be closer to investment practice. The primary objective is not statistical optimality, but to bridge the gap between research analyst and investor by concentrating on intuitive economic relations and transparency. Instead of providing estimated probabilities of being in a particular regime at any point in time, we can explicitly determine the prevailing phase of the business cycle, which enables us to define and compare several dynamic asset allocation strategies. We illustrate the DSAA framework with a sample of U.S. market data over the sixty year period from 1948 until 2007. Specifically, we combine four economic indicators (the credit spread, earnings yield, ISM and the unemployment rate) to identify four phases of the business cycle (expansion, slowdown, recession and recovery).[7] Because our business cycle phases do not depend on statistical properties of asset classes, we can easily consider a broad opportunity set instead of focusing on a limited set of assets. In addition to equities, bonds and cash we include small caps, value versus growth, credits and commodities in our analysis. Our framework is intended to help long-term investors design

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[4] Ang and Bekaert (2004) design a strategy which tries to exploit time-variation in returns using the switching framework of Hamilton (1989). They find that dynamic asset allocation across two regimes improves return for country allocation and for allocation across equities, bonds and cash.

[5] The approach can be extended to model more regimes. For example, Massimo and Timmermann (2007) statistically identify four regimes (crash, slow-growth, bull and recovery) to capture the joint distribution of stock and bond returns, which they use to derive a regime-based strategic asset allocation strategy. They also provide a good overview of the existing literature on this subject.

[6] An econometrician is needed to estimate the regime switching probabilities either with maximum likelihood or Bayesian techniques. The model must be kept simple with a limited number of assets because in the setup of Ang and Bekaert (2004) with 2 regimes and 6 assets, 19 parameters need to be estimated and one should check if the estimates are not ill-behaved.

[7] A detailed description of the model can be found in the appendix. In the robustness section we show that the results do not critically depend on the inclusion of any of these four factors.

a transparent and practically feasible dynamic strategic asset allocation strategy over the business cycle.

Empirically we find that the risk of a static SAA portfolio tends to increase during bad times, which is undesirable for a risk-averse investor. Besides risk, the average return of many assets is also found to be highly dependent on the prevailing economic phase. For example, most assets exhibit above-average returns during recessions and recoveries and below-average returns during expansions and slowdowns. We show that investors can improve the performance of their strategic asset allocation by taking into account the risk and return properties of each asset class conditional on the phase in the business cycle. We first examine a classic tactical asset allocation (TAA) approach, which concentrates on maximizing portfolio return during each economic phase. However, we find that this approach is suboptimal from a risk perspective, as it tends to increase risk systematically, and during bad times in particular. In order to address this concern we propose a dynamic strategic asset allocation (DSAA) approach which is successful at stabilizing portfolio risk across the business cycle, whilst, at the same time, offering the potential to enhance portfolio return. The key difference is that DSAA explicitly accounts for the interaction between tactical and strategic positions, which TAA ignores. We show that our empirical results are robust to changing the variables in the business cycle model, with considerable potential for further improvement. Finally, we argue that outsourcing a DSAA strategy to an external manager is more challenging than outsourcing a traditional TAA strategy. Investors could try to enforce their TAA managers to behave in a DSAA-consistent manner by imposing business cycle-dependent constraints, e.g. by setting time-varying asset class bandwidths. Alternatively, investors could decide to fully integrate DSAA into their own strategic asset allocation policy.

The paper proceeds as follows. The next section discusses our methodology; in particular our modeling of the business cycle and our definition of asset allocation strategies. Next we present the empirical results, including various robustness tests. The final section concludes.

6.2 Methodology

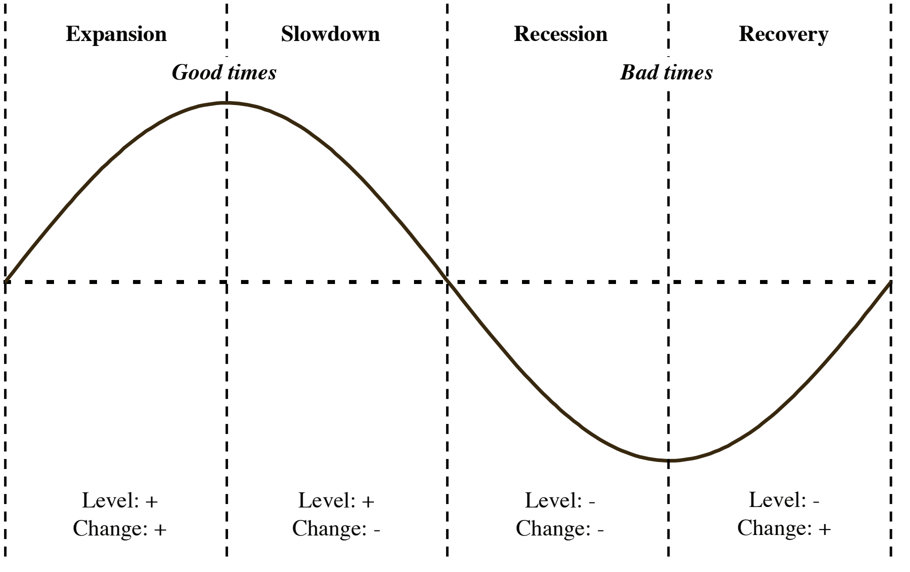
6.2.1 Modeling the business cycle

The NBER is well-known for determining official recessionary periods. NBER data is of little use for real-life dynamic asset allocation purposes though, as the NBER only classifies a period as either expansion or recession after the fact. Because of this hindsight, the NBER data is only suitable for *ex post* explanatory analyses and not for *ex ante* decision making. This is also recognized by Gorton and Rouwenhorst (2006), who use the NBER business cycle classification for gaining insight into the risk and return properties of commodities over the cycle.[8]

Figure 6.1

Conceptual illustration of business cycle with four phases

This graph conceptually illustrates economic conditions in the four phases of the business cycle.



In order to address this concern we propose an alternative, forward-looking business cycle indicator. Our indicator uses only information which is actually available ex ante and offers the additional advantage of resulting in a more balanced distribution of observations across economic phases. In the appendix we describe in detail how we combine four well-known economic indicators into one overall business cycle indicator, which can take on four different states. The four phases are schematically illustrated in Figure 6.1. In the

[8] Actually, Gorton and Rouwenhorst (2006) go even one step further by distinguishing between early and late expansions and early and late recessions, based on the *ex post* identification of each expansion and recession midpoint. This introduces an additional element of hindsight. Another drawback of this approach is that the frequency of the four resulting phases is quite unbalanced. Specifically, for our 60-year sample, early and late recessions in particular each contain only 8% of the data points, which is equivalent to fewer than 5 years of observations.

'expansion' phase the combination of 4 economic indicators is both positive and rising. In the 'slowdown' phase the level is still positive, but conditions are worsening. In the 'recession' phase both level and direction are negative, while in the 'recovery' phase the level is still negative, but improving. We will refer to the expansion and slowdown phase as 'good times' and recession and recovery as 'bad times'.

We also show that our business cycle indicator matches fairly well with the 'official' NBER business cycle classification, although we fully acknowledge that our method may be improved upon with a more sophisticated approach. However, the indicator suffices for the purposes of this paper, namely to compare various dynamic strategic asset allocation approaches based on a business cycle framework, and to estimate the potential for risk/return improvement that is offered by these approaches. Furthermore, we will show that our main results are robust to variations in the variable composition of the business cycle model.

6.2.2 Asset allocation strategies

We consider the following eight asset classes and investment styles: U.S. large cap equities, U.S. small cap equities, U.S. value equities, U.S. growth equities, U.S. credits, U.S. Treasuries, commodities and cash.[9] [10] All returns are in U.S. dollars. The sample period is from January 1948 through December 2007, spanning a total of 60 years. We use a monthly data frequency.

As a base-case strategic asset allocation policy, we consider a static strategic asset allocation portfolio, denoted by SAA, which every month invests 25% in large-cap equities, 25% in Treasuries and 25% in cash (core assets) and 5% in value equities, 5% in growth equities, 5% in small-cap equities, 5% in credits and 5% in commodities (satellite assets). Next we consider several dynamic asset allocation approaches that are based on our

[9] For large-cap equity returns we use the S&P 500 index. For value and growth returns we use the MSCI BARRA value and growth indices, which are available from February 1975 onwards, and prior to this we use data from Kenneth French (BV and BG). For small caps we use the Russell 2000 index, backfilled with small-cap return data from Kenneth French prior to January 1979. Credit returns are based on the Lehman U.S. Aggregate Corporate index, backfilled with data from Ibbotson (LT Corporate) prior to January 1973. U.S. Treasuries are based on the Lehman U.S. Aggregate Treasury index, backfilled with Ibbotson data (IT Government) prior to January 1973. Commodities are defined as the GSCI index, back-filled with the CRB spot index prior to January 1970. Cash is defined as the return on U.S. 30-day T-bills.

[10] As U.S. value equities and U.S. growth equities together (approximately) comprise U.S. large-cap equities, the latter asset class might be considered redundant. Nevertheless, we prefer to include each of these asset classes because it is convenient when, later on, we distinguish between core and satellite asset classes.

business cycle indicator. Each alternative is based on optimizing the asset allocation for each of the four phases separately, where for each alternative we use a different set of restrictions. In order to make a fair assessment of the added value of the optimized dynamic strategies, we not only compare them to our base-case static SAA portfolio, but also to a second SAA strategy, which is optimized full-sample for maximum return without taking into account the business cycle, i.e. assuming that asset returns are IID. We denote this strategy by SAA-O and impose the restriction that it has the same absolute risk as our base-case SAA portfolio and the same constraints on asset weights as our dynamic, business cycle-based strategies. In the spirit of Merton (1971), our SAA-O approach represents the solution to a myopic (one period) problem, whereas our dynamic asset allocation strategies, which explicitly assume that asset returns are not IID, represent intertemporal hedging demands based on the business cycle.[11] An overview is given in Table 6.1.

Table 6.1

Definition asset allocation strategies

This table gives an overview of the asset allocation strategies considered throughout this chapter.

	SAA-O	TAA	TAA-C	DSAA
Optimization approach				
Full-sample vs. phase-based	full-sample	phase-based	phase-based	phase-based
Asset weight restrictions				
Core assets	0-100%	0-100%	0-100%	0-100%
Satellite assets	0-10%	0-10%	0-10%	0-10%
Relative risk constraints				
Tracking error limit	-	1%	1%	1%
Absolute risk constraints				
Volatility limit full sample	σ_{SAA}*	-	σ_{SAA}*	σ_{SAA}*
Volatility limit for each phase	-	-	-	σ_{SAA}*

* measured full sample

Our first alternative that explicitly takes the business cycle into account is a tactical asset allocation (TAA) strategy, in which we optimize the portfolio in each phase of the cycle

[11] This argument is also given by Ang and Bekaert (2002) in the context of their regime switching model.

for maximum expected return, subject to a 1% tracking error limit. By using a tracking error constraint we ensure that the optimized portfolios do not exhibit extreme deviations from the static SAA reference portfolio, and we implicitly control transaction costs by forcing the optimizer to focus on the most attractive bets. The asset weights are required to be non-negative, add to 1 and not exceed 10% for the five satellite assets.[12] Weights for the three core assets are not constrained to a maximum value.

Because it turns out that the base-case TAA approach structurally increases portfolio risk, we also consider an alternative tactical asset allocation approach (TAA-C, denoting constrained TAA), which is identical to the TAA approach, except for the additional constraint that overall volatility does not exceed overall volatility of the static SAA portfolio. By definition, this approach prevents a structural increase in portfolio risk. However, it does not offer a solution for the tendency of the static SAA portfolio to become more risky during bad times. In fact, the TAA-C approach turns out to exacerbate this effect. In order to stabilize portfolio risk across the business cycle we therefore consider a final alternative, which we call a dynamic strategic asset allocation strategy (DSAA). With this approach we impose the additional restriction that not only overall portfolio volatility, but also volatility during each of the four phases does not exceed the overall volatility level of the static SAA.

All portfolio optimizations are full-sample because of data limitations. An approach based on in-sample strategy development followed by an out-of-sample test is practically infeasible.[13] With the full-sample approach we have an average of 15 years of data for each of the four economic phases, which is already a relatively short period of time for strategic asset allocation purposes. In other words, with an in-sample/out-of-sample approach the in-sample phase would already require most (or all) of our sample, leaving hardly (or no) remaining data for an out-of-sample test. Furthermore, as mentioned before, the primary objective of this paper is to present a framework for dynamic asset allocation, and the empirical data is only meant to illustrate the potential of such an approach. Our results do not aim to represent real-life investment strategies.

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[12] Jagannathan and Ma (2003) show that restricting portfolio weights is effectively a form of covariance matrix shrinkage. Diris, Palm and Schotman (2008) stress the importance of shrinkage when determining an asset allocation strategy.

[13] Goyal and Welch (2008) point out that many conditional variables may work well in-sample, but fail out-of-sample after they have been documented.

6.3 Results

6.3.1 Risk and return across the cycle

We begin our empirical analysis with investigating the risk and return of the assets in our sample across the different economic phases. Table 6.2 shows the correlations between several asset classes during each phase of the business cycle. These estimates are based on monthly data, but we note that quarterly data yields similar outcomes. The average correlations of equity with bonds, credits and commodities are 0.13, 0.29 and 0.00 respectively over the total 60-year sample period. Interestingly, however, we find that equity-bond correlations are negative during slowdowns and become positive during recessions and recoveries. This means that diversification benefits fade when they are needed most. By contrast, we find that during recoveries the correlation between equities and commodities becomes negative, indicating more opportunities for diversification.

Table 6.2

Key correlations across different economic phases

This table shows the correlation of bonds, credits and commodities with equities, both unconditionally (full sample) as well as conditional upon the prevailing phase of the economic cycle. The sample period is 1948 until 2007.

	Correlation with equities		
	Bonds	Credits	Comm
Full sample	0.13	0.29	0.00
By phase			
Expansion	0.04	0.09	0.02
Slowdown	-0.16	0.12	0.02
Recession	0.15	0.35	0.02
Recovery	0.38	0.45	-0.12

Table 6.3 shows the annualized volatility of each asset class, as well as the static SAA portfolio, across the different phases. We find that risk tends to be highest during recessions and recoveries (bad times). The full sample volatility of the static SAA portfolio is 6.2%, but this number varies between 5.6% in good times and 6.6% in bad times. This time-varying risk profile is mainly caused by (1) the increased risk of government and corporate bonds in bad times and (2) the increased equity-bond correlation during bad

times discussed before. During recessions the volatility of commodities decreases somewhat, and during recoveries the correlation of commodities with other asset classes becomes more negative. Equities show limited time-variation in risk across the four phases in the business cycle.

Table 6.3

Risk of asset classes for each economic phase

This table shows the risk of each asset class, both unconditionally (full sample) as well as conditional upon the prevailing phase of the economic cycle. The sample period is 1948 until 2007. Risk is defined as annualized volatility.

	Equity	Value	Growth	Small	Credits	Bonds	Comm	*SAA*
Full sample	14.2%	14.0%	15.4%	18.9%	6.4%	4.7%	15.6%	*6.2%*
By phase								
Expansion	13.8%	14.0%	14.6%	18.7%	4.5%	3.5%	14.0%	*5.6%*
Slowdown	13.7%	13.8%	15.2%	19.8%	5.1%	3.9%	18.1%	*5.7%*
Recession	14.6%	14.0%	16.0%	18.7%	8.2%	5.6%	15.9%	*6.6%*
Recovery	13.9%	13.3%	15.3%	18.5%	6.4%	5.1%	15.7%	*6.4%*

Table 6.4 shows the excess (log-)returns of each asset class across the four phases. The SAA portfolio yields an average return of 2.9% in excess of cash, but this return varies between 0.5% during slowdowns and 4.8% during recessions. This result is driven by the fact that equity returns are highest during recessions and lowest during slowdowns. This suggests that financial markets run ahead of the business cycle by about one phase. In other words, when the real economy slows down, equity markets already show disappointing returns because of the anticipated recession, while equity markets are already recovering when the real economy is still in recession. This implies that financial markets do not concentrate on current economic conditions, but also take into account expected future economic conditions. An important observation is therefore that bad times for the economy are not necessarily bad times for investors! During bad economic times not only risks are higher, but also returns tend to be higher.

Table 6.4

Return of asset classes for each economic phase

This table shows the annualized return in excess of the risk-free rate of return for each asset class, both unconditionally (full sample) as well as conditional upon the prevailing phase of the economic cycle. The sample period is 1948 until 2007.

	Equity	Value	Growth	Small	Credits	Bonds	Comm	*SAA*
Full sample	5.6%	6.4%	4.7%	6.6%	0.5%	0.6%	1.3%	*2.9%*
By phase								
Expansion	3.7%	3.2%	3.9%	0.9%	-1.0%	-0.4%	5.7%	*1.8%*
Slowdown	0.2%	1.9%	-1.6%	2.9%	-3.0%	0.1%	-0.2%	*0.5%*
Recession	10.2%	11.1%	9.0%	12.7%	1.6%	1.4%	-3.7%	*4.8%*
Recovery	5.1%	7.1%	3.3%	9.4%	3.0%	1.2%	6.1%	*3.4%*

Interestingly, both the value premium (value versus growth) and the size premium (small versus large) are negative during expansions, while being positive during the other three phases of the cycle. Also noteworthy is the lack of a credit risk premium (credits versus Treasuries) in our sample. Credits outperform government bonds during recessions and recoveries, but underperform during expansions and slowdowns. Commodities deliver high returns during expansions and recoveries, whilst lagging during slowdowns and recessions. In sum, we observe various pronounced cyclical patterns in the return characteristics of the different asset classes, which motivates the examination of business cycle-based asset allocation strategies.

6.3.2 Business cycle-based asset allocation

In this section we compare the static SAA approach with the business cycle-based asset allocation strategies defined in the methodology section. In Table 6.5 we show the optimized portfolio weights and in Table 6.6 we show the risk/return characteristics of the various approaches.

The SAA-O full-sample optimized portfolio exploits the value and small-cap premium to the maximum extent possible, and it makes maximum use of the attractive risk/return properties of commodities. Nevertheless, it only manages to improve the excess return by a statistically insignificant 0.20%, whilst also failing at stabilizing the risk of the portfolio over the cycle.

Table 6.5

Weights of optimized business cycle-based allocation strategies

This table shows the optimized weights for the asset classes based on the different asset allocation strategies as defined in Table 6.1. The sample period is 1948 until 2007.

	Equity	Value	Growth	Small	Credits	Bonds	Comm	Rf
SAA								
Static base-case	25%	5%	5%	5%	5%	25%	5%	25%
SAA-O								
Static optimized	19%	10%		10%		25%	10%	26%
TAA								
Expansion	39%		3%	2%		26%	10%	21%
Slowdown	22%	10%		9%		31%	5%	23%
Recession	29%	10%		8%		34%	3%	15%
Recovery	24%	10%		10%	10%	23%	9%	14%
TAA-C								
Expansion	34%		4%			19%	10%	33%
Slowdown	14%	10%		10%		27%	4%	35%
Recession	25%	10%		9%		31%	1%	24%
Recovery	19%	10%		10%	10%	20%	10%	21%
DSAA								
Expansion	39%		5%			21%	10%	25%
Slowdown	19%	10%		10%		31%	5%	25%
Recession	20%	10%		9%		27%		34%
Recovery	18%	10%		10%	10%	19%	10%	23%

The first dynamic allocation strategy which we consider is the base-case TAA approach, which, for each phase, selects a portfolio which is optimized for highest expected return, taking into account the restrictions outlined in the methodology section. The average excess return of the TAA approach is 3.71% per annum, compared to 2.90% for the static SAA approach. The difference is 0.81%, which, given the tracking error budget of 1%, translates into an information ratio of 0.81. This performance is not only economically significant, but also highly statistically significant, with an associated t-value of 6.29. The return differential ranges from 0.45% during slowdown phases to 1.08% during recessions. However, not only portfolio return, but also portfolio risk is increased. In fact, the TAA portfolio exhibits a systematically higher level of risk than the SAA reference portfolio.

Compared to the static SAA portfolio, overall volatility increases from 6.17% to 6.82%, and volatility is also higher in each of the four separate economic phases. One of the reasons for this is that the TAA portfolios systematically overweight equities and underweight cash compared to the static SAA portfolio. In other words, the additional return generated by the TAA approach is, at least partly, simply a reward for additional beta exposures instead of true alpha. In fact, the outperformance of the TAA portfolio vis-à-vis the SAA portfolio exhibits a correlation of 0.62 with the absolute return of the SAA portfolio. The importance of making the distinction between performance as a result of true alpha instead of implicit beta in the context of tactical asset allocation is also stressed by Lee (2000).

In order to address this concern we consider the TAA-C approach, which is specifically aimed at preventing an increase in overall portfolio risk. Table 6.6 shows that overall portfolio risk of the TAA-C strategy is indeed equal to that of the static SAA strategy. Consistent with this, the structural overweight of equities observed for the TAA strategy is not present with the TAA-C strategy. The average excess return improvement drops to 0.61% (equivalent to an information ratio of 0.61, with a t-value of 4.70), ranging from 0.43% during expansions to 0.81% during recoveries. During slowdowns, recessions and recoveries, the TAA-C strategy overweights value stocks and small-caps, and underweights growth stocks. During expansions, the strategy underweights value and small-caps and is neutral on growth stocks. Credits are always underweighted except during recoveries. Commodities are overweighted during expansions and recoveries, neutral during slowdowns and underweighted during recessions.

Although the TAA-C approach is successful at controlling overall portfolio risk, it does not succeed in achieving a stable risk. Both the static SAA strategy and the TAA-C strategy exhibit pronounced time-varying risk across economic phases. For the static SAA strategy this is simply due to the time-varying risk characteristics of asset classes. The TAA-C strategy, however, goes one step further by actively reducing risk during low return phases (expansions and slowdowns), in order to be able to take on more risk during the highest return phase (recessions). In other words, instead of countering the tendency of the SAA strategy to exhibit more risk during bad economic times, the TAA-C strategy turns out to exacerbate this behaviour. As mentioned before, this is particularly undesirable for a risk-averse investor, see Cochrane (1999).

In order to address this concern we propose an approach which we call dynamic strategic asset allocation, or DSAA. This approach is specifically designed to stabilize risk across the business cycle. Specifically, the portfolios are optimized subject to the

Table 6.6

Risk/return features of optimized business cycle-based allocation strategies

This table shows the return and risk characteristics for the different asset allocation strategies. The sample period is 1948 until 2007. Risk is defined as annualized volatility and return is excess return over cash. Outperformance is defined as the return difference with the SAA reference portfolio. The sample period is 1948 until 2007.

Panel A: Return

	SAA	SAA-O	TAA	TAA-C	DSAA
Full sample					
Return	2.90%	3.10%	3.71%	3.51%	3.38%
Outperformance		0.20%	0.81%	0.61%	0.48%
(t-statistic)		(1.54)	(6.29)	(4.70)	(3.71)
By regime					
Expansion	1.78%	1.98%	2.35%	2.21%	2.44%
Slowdown	0.45%	0.99%	0.90%	0.90%	0.95%
Recession	4.80%	4.75%	5.88%	5.55%	4.97%
Recovery	3.37%	3.76%	4.42%	4.18%	4.12%

Panel B: Risk

	SAA	SAA-O	TAA	TAA-C	DSAA
Full sample	6.17%	6.17%	6.82%	6.17%	6.17%
By regime					
Expansion	5.60%	5.70%	6.07%	5.35%	6.17%
Slowdown	5.68%	5.98%	5.83%	4.95%	5.66%
Recession	6.55%	6.46%	7.54%	6.98%	6.17%
Recovery	6.36%	6.16%	7.06%	6.32%	6.17%

constraint that not only overall volatility, but also volatility during each phase does not exceed 6.17%. Looking at the resulting portfolios, we observe that the main change compared to the TAA-C approach is the weight of equities, which is now chosen in such a way that risk across different economic phases is stabilized. The average return enhancement is equal to 0.48%, implying an information ratio of 0.48 (with a t-value of 3.71). The return improvement ranges between 0.50% and 0.75% during expansions, slowdowns and recoveries. During recessions, the main improvement is not an increase in expected return (which is enhanced by only 0.17% in this phase), but a reduction of risk, as volatility can be seen to drop from 6.55% to 6.17%. Stable risk across the business cycle is desirable for a risk-averse investor with a constant risk budget. To summarize, the DSAA approach is able to stabilize risk across the business cycle, whilst, at the same time, improving expected return.

6.3.3 Robustness

The case for dynamic strategic asset allocation hinges on two premises, namely the ability to identify time-varying risk and time-varying return opportunities. In reality, the latter condition is likely to be most challenging. However, even if expected returns are considered to be unpredictable, there remains a case for DSAA, albeit a simplified variant which is solely aimed at stabilizing portfolio risk. In this section we will examine the robustness of our finding that, at the very least, a business cycle-based approach is able to identify time-varying risk characteristics and can be used to adjust the portfolio composition accordingly.

We begin by examining the risk of the asset classes in our sample during official NBER expansions and contractions. The results are shown in Table 6.7. Consistent with the results for our business cycle model, we observe that the risk of each class is significantly higher during 'bad times' (NBER contractions) compared to 'good times' (NBER expansions). This provides corroborating evidence for the existence of time-varying risk that is linked to the business cycle.

Table 6.7

Risk of asset classes conditional upon NBER economic phase

This table shows the risk of each asset class conditional upon the economic phase as defined by the National Bureau of Economic Research. Risk is defined as annualized volatility. The sample period is 1948 until 2007.

	Equity	Value	Growth	Small	Credits	Bonds	Comm	*SAA*
NBER expansions	13.3%	13.1%	14.4%	17.5%	5.5%	4.2%	14.4%	*5.7%*
NBER contractions	18.1%	17.6%	19.6%	24.8%	9.8%	6.3%	20.7%	*8.2%*

The business cycle model that has been used throughout this paper appears to be effective at identifying time-varying risk *ex ante*. We may wonder, however, how sensitive this result is to our choice of variables that, together, comprise the business cycle model.

Therefore we examined the effects of leaving out any one of the four variables in the business cycle-model. The results of this analysis are shown in Table 6.8. We observe that removing any one of the four variables in the business cycle model does not degrade its ability to identify time-varying risk. If anything, this aspect of the model appears to improve somewhat, as the dispersion in volatility across economic phases tends to widen.

If DSAA is applied with the sole objective to stabilize portfolio risk, one might consider tailoring the business cycle model specifically towards that purpose. Empirically volatility is often found to be persistent, i.e. if volatility has recently been high (low), it is likely to remain high (low) in the following period. The literature which takes a purely statistical approach towards identifying regimes in the time-series properties of asset class returns, also tends to find alternating periods with high and low volatility. Inspired by these results we examined 12-month realized equity volatility as a potential additional (or alternative) factor for the business cycle model.[14] Consistent with what we would expect a priori, we find that 12-month realized equity volatility is above average and increasing during NBER contractions. The last column in Table 6.8 shows that when the variable is added to our base-case business cycle model, it becomes better at identifying time-varying risk characteristics. If 12-month realized equity volatility is added as a fifth factor, the spread between the maximum and minimum volatility across economic phases increases from less than 1% to over 1.5%.

Table 6.8

Regime model sensitivity analysis

This table shows SAA portfolio risk across the business cycle for alternative business cycle models. Risk is defined as annualized volatility. The sample period is 1948 until 2007.

	Base case	Excluding credit spread	Excluding earnings yield	Excluding ISM	Excluding unemploy-ment	Including equity volatility
Expansion	5.60%	5.54%	5.14%	5.25%	5.48%	5.31%
Peak	5.68%	5.80%	5.84%	6.09%	5.65%	5.39%
Recession	6.55%	6.53%	6.67%	6.52%	6.58%	6.83%
Recovery	6.36%	6.56%	6.78%	6.62%	6.36%	6.48%

[14] A forward-looking implied volatility indicator such as VIX might be even more appealing, but the data for such variables is not available with a history of sixty years.

We conclude that, if the primary objective of a business cycle approach is considered to be stabilizing portfolio risk over time, our base-case business cycle model does not paint an overly optimistic picture, as we find that even stronger results may be obtained by considering additional variables.

6.4 Summary and implications

We propose a practical investment framework for dynamic asset allocation across the business cycle, which we illustrate with a sample of data for the U.S. market over the period from 1948 until 2007. We construct a business cycle indicator based on a combination of four well-known economic variables, which can take on four different states. The business cycle indicator is found to relate reasonably well to the official NBER business cycle. Our first empirical result is that the risk and return properties of asset classes are highly dependent on the prevailing economic phase. This finding motivates the examination of various dynamic asset allocation strategies. As a benchmark we take a traditional SAA portfolio which has static weights, but a time-varying risk/return profile over the business cycle,. In particular, risk tends to go up in bad times, which is undesirable for a risk-averse investor. An alternative, full-sample optimized static SAA portfolio is neither able to stabilize risk across the cycle, nor does it succeed in significantly enhancing return.

One way investors can exploit the business cycle is by developing a TAA strategy, which is designed for a maximum outperformance in each phase of the cycle. The drawback of this approach is that absolute portfolio risk is increased systematically, and in particular, once again, in bad times. In order to stabilize absolute portfolio risk and simultaneously, enhance portfolio returns, we propose a dynamic strategic asset allocation approach. We have shown that the proposed DSAA approach is robust to variations in the variable composition of the business cycle model and that the approach can easily be extended with different economic variables and/or additional assets. The DSAA framework is intended to bridge the gap between research analyst and investor by concentrating on intuitive economic relations and transparency, contrary to existing statistically driven techniques such as Markov regime-switching models. For investors who are skeptical towards exploiting time-variation in asset returns we have shown that DSAA can still serve as a robust tool for stabilizing portfolio risk across the cycle, with considerable potential for further improvement.

Interestingly, the aim for stable absolute performance across the business cycle through dynamic strategic asset allocation leads to markedly different portfolios and performance characteristics than the aim for stable outperformance through tactical asset allocation. Absolute return investors bring down risk during bad times, while relative return investors increase risk during bad times. These opposing outcomes imply that it is essential to clearly specify the investment objectives, consistent with the finding by Binsbergen, Koijen and Brandt (2008) that a decentralized investment approach can lead to suboptimal portfolios.

Institutional investors who would like to implement a business cycle-based allocation approach need to choose between internal versus external management. In case of outsourcing the challenge is to align the investment objectives of the investor with those of the external manager. Outsourcing is fairly straightforward if the objective is simply to enhance return. As we have seen, however, a TAA approach which concentrates on maximizing returns can have undesired consequences for the overall risk profile of the portfolio. A DSAA strategy with overall and business cycle-dependent constraints on absolute portfolio risk addresses this concern, but outsourcing this to an external manager is likely to be more challenging in practice. Risk monitoring should become more sophisticated and an *ex post* performance evaluation of the external manager should not focus solely on the realized outperformance and tracking error of the manager, but also evaluate if the manager has been successful at stabilizing overall portfolio risk. In order to avoid these practical complexities investors could decide to fully integrate DSAA into their internal strategic investment policy. Alternatively, investors might enforce their TAA managers to behave in a DSAA-consistent manner by imposing business cycle-dependent constraints (e.g. bandwidths) on the exposure to each asset class. For example, in case a high-risk economic phase is identified, a TAA manager might be restricted from overweighting high-risk assets such as equities.

Appendix to chapter 6: Construction of business cycle indicator

The philosophy behind our business cycle indicator is to combine a limited number of economically relevant variables using a simple and transparent model structure, aiming for a reasonably good match with the official business cycle as classified by the NBER. We acknowledge that by using a more sophisticated approach it would probably be possible to develop a superior model, but that is not our main objective. The number of possible variables is limited because we impose the requirement that a data history of at least 60 years should be available. We consider two market variables that have already been linked to the business cycle in the literature on conditional asset pricing, namely the credit spread (Chen, Roll and Ross, 1986) and the earnings yield (Campbell & Shiller, 1987), and two macro-economic variables that are also clearly linked to the cycle, namely the ISM (which is designed to be a leading economic indicator) and the unemployment rate (which is a widely used lagging economic indicator).

The credit spread is defined as the difference between Baa and Aaa corporate bond spreads from Moody's and the earnings yield is the E/P ratio of the S&P500. A high credit spread or high earnings yield indicates 'contraction', while low spreads or yields indicate 'expansion'. The ISM is the seasonally adjusted U.S. manufacturers' survey production index and the unemployment rate is the seasonally adjusted U.S. unemployment rate from the Bureau of Labor Statistics.[15] An ISM value above 0.50 or low unemployment indicates 'expansion' and an ISM below 0.50 or high unemployment indicates 'contraction'. All data are obtained from Datastream and prior to 1970 backfilled using the FRED database[16] and, for P/E, Robert Shiller's database.[17]

Figure A6.1 shows the monthly data for each of our four business cycle indicators, defined in the data section, over the full sample of 60 years. We observe different cycle lengths for each of the four factors. For the credit spread level we observe three main phases: the credit spread is between 50-125 during most of the 1950s and 1960s, rising to 75-300 during the 1970s and 1980s and falling back to 50-125 starting from the 1990s onwards. The earnings yield can be described in four phases. It varies between 8-16% from 1948-1958, falling to 4-8% during 1959-1973, going up again to 8-15% during the 1973-1985 period, and then varying between 2-8% during the 1985-2007 period. The ISM factor fluctuates much more frequently, passing the neutral level of 0.50 either from either above

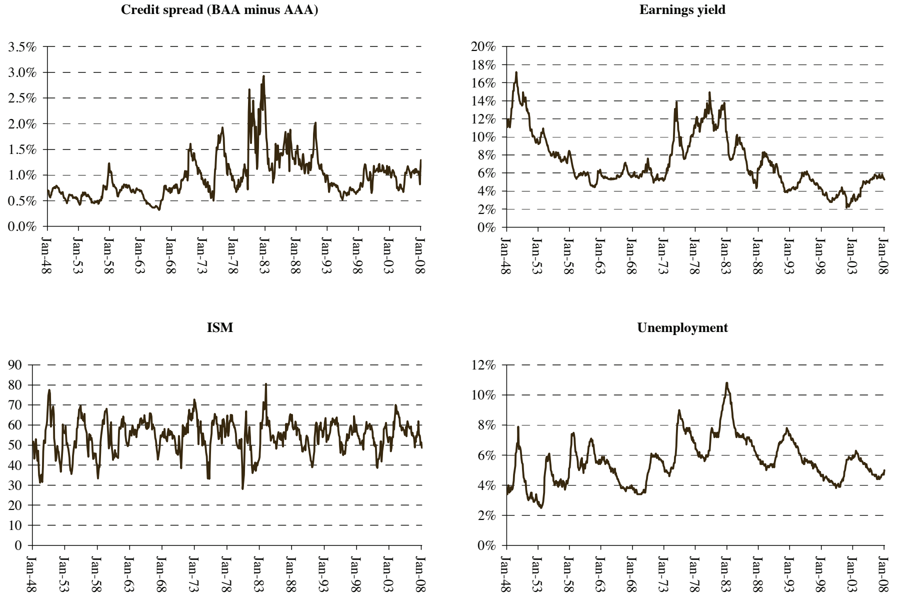
[15] The ISM data and unemployment data are final figures and could differ from the preliminary figures published earlier.
[16] http://research.stlouisfed.org/fred2
[17] http://www.econ.yale.edu/~shiller/data.htm

or below about 30 times over this sample period. Finally, we observe that the unemployment rate passes the median value of 5.5% about 15 times. Thus the different cycles last between 2-20 years, depending on the variable under consideration.

Figure A6.1

Time-series of economic indicators

This figure shows the time-series for the economic indicators used in the business cycle model. Monthly observations over the sixty year period from 1948 until 2007.



We proceed by relating the economic indicators to the NBER business cycle indicator. NBER defines 114 out of the total 720 months in our sample as contraction period, or 16% of all observations.[18] It is important to note that NBER classifies a contraction with hindsight, while our business cycle indicator only uses information available prior to the next month. Table A6.1 shows the average level and 1-year change of each indicator during the full sample and during NBER recession periods.

[18] http://www.nber.org/cycles.html

Table A6.1

Characteristics of economic indicators

This table shows the level and 1-year change of the economic indicators, both full sample (720 months) and during recessionary periods as defined by the NBER (114 months).

	Full sample		NBER Contractions	
	Level	Standard deviation	Level	1-year change
Credit spread	96.1	42.5	120	+27.8
Earnings yield (%)	7.2	3.1	9.5	+1.3
ISM index	54.5	8.0	43.2	-10.8
Unemployment (%)	5.6	1.5	6.0	+1.2

We observe that during NBER contraction periods (1) the credit spread is high and increasing, (2) earnings yield is high and increasing, (3) ISM is low and decreasing, and (4) unemployment is high and increasing. Thus we find that both the level and the 1-year change contain information about economic conditions. During NBER contraction periods, we observe that the four indicators, both in terms of level and change, deviate by about 0.5 to 1.0 standard deviations from their long-term average values.

In order to obtain a robust and broad indication of the condition of the U.S. economy, we proceed by combining the four economic factors into one overall business cycle score.[19] We note that the main findings in this paper are robust to leaving out any one of the four indicators. We standardize the four economic variables by deducting their full-sample medians[20] and dividing by their full sample standard deviations. To limit the impact of outliers and individual factors we further cap the individual z-scores to a maximum of +3 and a minimum of -3. Finally, we combine the individual z-scores into one overall score by adding the individual scores and dividing by the square root of 4.[21]

Based on the combined indicator we define four economic phases. In the 'expansion' phase the combined indicator is both positive and increasing. In the 'slowdown' phase the level is still positive, but conditions are worsening. In the 'recession' phase both level and direction are negative, while in the 'recovery' phase the level is still negative, but improving. This classification is consistent with Gorton and

[19] We would like to stress that other macro or market factors can also be used. These four factors are used to illustrate how economic data can be used to construct a dynamic SAA framework.

[20] We use median instead of mean in order to reduce the impact of outliers on the resulting z-scores.

[21] If the factors are normally distributed and uncorrelated, then the economic score is also standard normally distributed. However, in practice we observe that the factors are positively correlated especially during stressful periods.

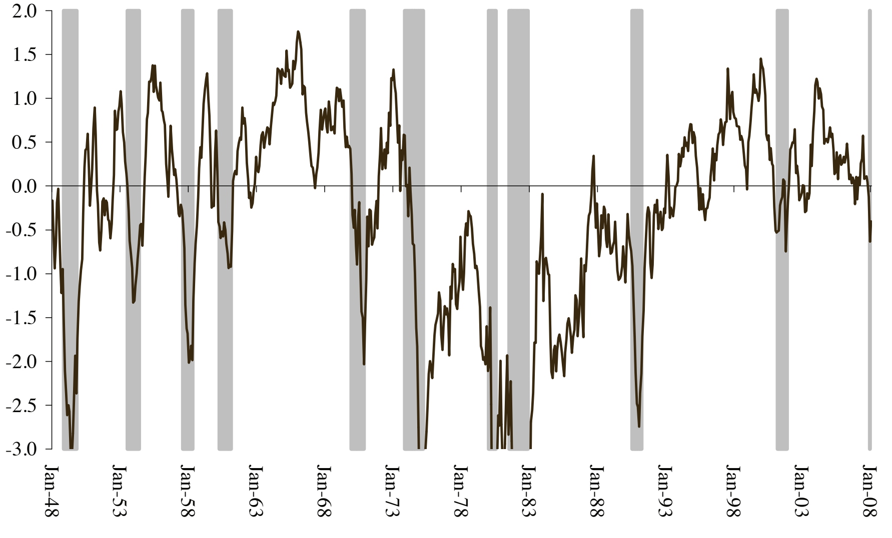
Rouwenhorst (2006), who differentiate between early and late expansion and early and late recession using NBER slowdown and through data. However, the advantages of our approach are that (i) it is applicable in practice as the required data is readily available ex ante and (ii) the monthly observations are more evenly distributed across economic phases leading to more statistical power.

Figure A6.2 shows the historical values of our economic indicator together with the NBER contraction periods (shaded areas) for the full sample period from 1948 to 2007. The economic indicator varies between +1.8 (1965) and -5.0 (1982). A positive score indicates ‘good times’, while a negative score indicates ‘bad times’. In general we find that gradual increases in economic conditions are followed by abrupt downside shocks. The figure shows that a negative and/or falling indicator is associated with contraction periods. This finding is in line with the results of Table A6.1.

Figure A6.2

Time-series of the combined economic indicator

This graph shows the time-series of the combined economic indicator. NBER contraction periods are highlighted in gray. Monthly observations over the sixty year period from 1948 until 2007.



We translate the combined economic indicator into four phases depending on its (i) level and (ii) 1-year change. For example, at the end of 2007 both the level and change were negative, which implies that the following period is classified as a recession phase. Table A6.2 shows the distribution of the four economic phases and the accompanying transition matrix. The expansion and recession phases occur more often than slowdown and recovery phases. This can be explained by our earlier observation that gradual increases in economic conditions tend to be followed by rather abrupt declines in economic conditions. This asymmetry causes slowdowns in particular to be rather short-lived. The transition matrix shows that the probability of staying in one phase from month to month is between 83-93%, while the probability of moving to another phase is 7-17%. This translates into an average duration of each phase in the business cycle of about 9 months.[22]

Table A6.2

Distribution of four economic phases and transition matrix

This table shows the distribution of the combined economic indicator over the four economic phases and transition probabilities of migrating from one phase to another phase.

	Transition Matrix				Total	NBER
From\To	Expansion	Slowdown	Recession	Recovery	number	recessions
Expansion	93%	3%	-	3%	230	1
Slowdown	6%	83%	11%	-	95	6
Recession	2%	3%	90%	4%	238	101
Recovery	4%	-	8%	88%	144	6

When our business cycle model indicates a state of recession, there is a 42% chance that NBER will later on classify this month as a part of a contraction period. We find that 90% of all NBER contraction periods fall within the model recession phase, while 10% falls in either slowdown or recovery. Thus, NBER contraction periods coincide strongly with our economic indicator being negative and falling. All major contraction mid-points are predicted correctly, although the exact slowdown (start) and trough (end) are sometimes classified differently. Interestingly, the recession of the early 1990s is also correctly predicted. Stock and Watson (1992) argue that most leading indicators have difficulty predicting this particular contraction period.

[22] In order to limit the transition of one phase to another due to noise (signal flip-flopping), we include an absolute threshold of 0.10. For example, if the combined indicator is +0.05 then this is within the bandwidth of -0.10 and +0.10 which means that we do not change phase and keep the same phase as in the previous month. The same threshold applies for 1-year changes which should also exceed an absolute value of 0.10.

To summarize, we have proposed a framework which can be used to translate economic variables into a business cycle indicator which can take on four different states. With the four variables proposed in this paper, the business cycle indicator is found to match reasonably well with the official business cycle as reported by the NBER.

7 The Performance of European Passive Funds[1]

7.1 Introduction

In this chapter we investigate the performance of index mutual funds and exchange-traded funds (ETFs) that are listed in Europe. Despite the enormous size of the European mutual fund industry (more than USD 6 trillion in 2008) and the increasing popularity of passive investing in Europe, research on the performance of European passively managed funds has generally been lacking and important questions remain unanswered.[2] For example, do the results found in the academic literature for U.S. index funds and ETFs carry over directly to European funds? In particular, do European index funds and ETFs underperform their benchmarks by the magnitude of their expenses? And to what extent do regulatory issues, such as taxes, play a different role in Europe than they do in the United States?

Studies on the performance of U.S. passive funds report that fund returns are predictable with a high degree of accuracy and that there is a one-to-one negative relation between fund returns and their expenses [see, e.g., Elton, Gruber, and Busse (2004)]. Consistent with these studies, we find that expense ratios are an important determinant of European passive-fund returns. However, we document two notable observations that cannot be explained by fund expense ratios. First, that European index funds and ETFs fall short of the (gross) total returns of their benchmark indexes by 50 to 150 basis points per annum, which is significantly more than the shortfalls reported for U.S. passive funds. This shortfall is also more than we would expect based on the funds' reported expenses. An illustration of this remarkable observation is the performance differential between the Vanguard S&P 500 index funds that are listed in the U.S. and Ireland. Even though the funds invest in the same stocks and are managed by the same family, the European fund systematically underperforms the U.S. funds by 70 basis points, while the difference in expense ratios is only 20 basis points.[3]

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[1] This paper is based on Blitz, Huij and Swinkels (2009). We would like to thank an anonymous referee, John Doukas, Keith Brown, Sander Haaijer, Angelien Kemna and seminar participants at Erasmus University for valuable comments. We thank Sandra Sizer for excellent editorial assistance.
[2] While European funds are an under-researched area, there are a few studies that investigate actively managed European funds, including Otten and Bams (2002, 2007).
[3] The reported performance differential between the Vanguard S&P500 index funds that are listed in the US and Ireland are computed over the period January 2003 to December 2008.

Second, we observe substantial performance differences between funds that track different benchmark indexes that seem unrelated to expense ratios. Even though funds that track the major stock-market indexes in the U.S and Europe generally have similar expenses compared to funds that track the major Japanese indexes, it appears that the latter display consistently better performance. Strikingly, passive funds that track the S&P 500 or MSCI USA indexes underperform their benchmarks by more than 120 basis points per year, while passive funds that track the MSCI Japan or Topix indexes underperform by only about 50 basis points.

We show that these two observations can be almost entirely attributed to dividend taxation. Because local revenue authorities impose dividend withholding taxes, European mutual funds often do not receive the full dividends on their investments, for example when investing in U.S. equities. However, when total- return benchmarks are constructed, the default assumption is that dividends are fully reinvested. Because expense ratios do not take into account the performance loss due to dividend taxes, the differences that arise between the returns of European funds and their benchmarks cannot be explained by fund expense ratios.

By taking dividend taxes into account we can explain most of the underperformance of the passive funds in our sample. The explanatory power of dividend taxes as a determinant of the performance of European index funds and ETFs is at least on par with fund expense ratios. We find that, on average, fund expense ratios contribute -56 basis points per year to fund performance, while the impact of dividend taxes amounts to -48 basis points. Moreover, dividend taxes almost completely explain the differences we observe in performance between funds that track different benchmark indexes. Our results indicate that the substantial underperformance of passive funds that track the major stock market indexes in the United States and Europe can be attributed to the relatively higher impact of dividend taxation in these areas.

The funds in our sample also exhibit significant time variation in their performance, which we attribute to dividend taxation. This time variation is particularly strong for funds that invest in Europe. When we split our sample into months with a high or a low dividend-tax impact, we find that passive funds fall short of their benchmarks by 51 basis points per year during the low-impact subsample, but that this figure is close to 100 basis points during the high-impact subsample. This observation provides additional evidence supporting the critical importance of dividend taxes for the performance of European index funds and ETFs.

Our paper contributes to the existing literature in at least four important ways. First, we provide new insights into the performance of European index funds and ETFs.

Most current studies are based on U.S. funds and attribute fund performance to fund expenses, which are measured by expense ratios and organizational structures [see, e.g., Elton, Gruber, Comer, and Li (2002); Poterba and Shoven (2002); Blume and Edelen (2004); Elton, Gruber, and Busse (2004); Gastineau (2002, 2004); and Agapova (2009)]. However, it is currently not known what the relative importance of these factors is in explaining the performance of passive funds listed in Europe.

Second, our results suggest that investors should refine their measures of fund costs.[4] Although its name suggests that the total expense ratio covers all relevant costs, in fact the total-expense ratio ignores a cost component that turns out to be very important for a large group of funds. For the funds in our sample, the impact of dividend taxes on performance is about as large as that of all other expenses combined.

Third, our results have implications for the performance evaluation of actively managed funds that are subject to dividend withholding taxes. The typical approach to measuring managerial skill is to test if fund alphas are different from zero. However, we argue that this approach may paint a picture that is too pessimistic in certain cases about the value added by active management. The benchmark indexes against which actively managed funds are typically evaluated ignore the significant costs of dividend taxation, thus projecting return levels that cannot be achieved by passively managed funds. Therefore, it would be more even-handed to set the hurdle rate for actively managed funds equal to the returns that passive funds are actually able to realize. This argument applies not only to European mutual funds, but also to all funds that are subject to dividend taxes, including, for example, U.S.-listed mutual funds that invest in international or emerging markets.

Fourth, and finally, our results indicate that ignoring dividend taxes can lead not only to biased inferences about mutual fund performance on aggregate, but can also distort relative fund comparisons. Estimated alphas of funds that invest in regions in which the impact of dividend taxation is relatively high are underestimated if the employed benchmarks assume that dividends are fully reinvested. This implication also goes beyond our sample of European-listed funds and carries over to, for example, U.S.-listed funds that invest abroad.

In Section 2 we describe the data that we use in our analysis. Section 3 contains the empirical results, and in Section 4 we discuss the implications of our findings.

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[4] Ramos (2009) observes a large dispersion in fund fees across different countries. Taking dividend taxation into account will likely further increase this dispersion. Korkeamaki and Smythe (2004) analyze the competitiveness of the Finnish mutual fund market by analyzing the fund's expense ratio and do not separately measure tax efficiency.

7.2 Data

In our analysis of passive funds we include both traditional index mutual funds and the more novel ETFs, that are listed in Europe. According to Barclays[5], at the end of July 2009, the estimated number of ETFs globally numbered 1,678, with roughly 3,100 listings and over $850 billion assets under management. The number of ETFs in Europe was 753 compared to 706 for the United States. The total amount invested in ETFs is estimated to be $183 billion in Europe and $582 billion in the United States.

We use a sample of passive funds listed in Europe that invest in all major global stock markets. We start by creating a comprehensive list of passive funds. To do so, we search Thomson Financial Datastream and the Morningstar websites for all funds listed in Europe with names that include the word "index" or "idx", and by considering all available ETFs. We clean this sample by removing enhanced indexing funds, institutional funds, and insurance funds. To obtain the investment policy of the fund (passive or enhanced) and the clientele that the fund is allowed to attract (retail or institutional), we check the Morningstar website and the website of the provider of these funds on a case-by-case basis. For insurance funds, the cost load may be unclear, since costs may be charged within the insurance contract instead of within the fund itself.

Next, we filter for funds that track one of the broadly diversified equity market indexes that are of primary importance for a global investor who is looking for passive equity market exposure. These indexes are the S&P 500 or MSCI USA (United States equities), MSCI Europe (European equities), MSCI Japan, or Topix (Japanese equities), MSCI World (global equities) and MSCI Emerging Markets (emerging markets equities).[6] Most index funds are based on one of these indexes, but many ETFs tend to be based on either thematic indexes or on narrow (e.g., single country or sector) indexes.[7] Although such funds can be of interest to investors who wish to obtain easy access to a certain investment theme, they are not the focus of our study so we remove them from our sample. We obtain expense ratios for the funds from the Morningstar European websites or from their parent firm websites, and total return data for the funds and their benchmark indexes from Thomson Financial Datastream. We note that we do not account for front- or back-end load fees that might be charged for different share classes of the mutual funds.

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[5] ETF Landscape Industry Review, August 2009

[6] We do not include funds which use one of the Nikkei indexes (e.g., Nikkei 225 or Nikkei 300) as their benchmark, because of the fact that proper total return series are not available for these indexes.

[7] Ranaldo and Häberle (2007) advocate the use of broadly diversified indexes for passive investors, as they consider narrow indices active strategies because of their selection rules and resulting turnover.

We include all the leading providers in our final sample, which comprises index mutual funds from Vanguard, State Street Global Advisors (SSgA), Crédit Agricole (CAAM), Pictet, BNY Mellon / Mellon, Coutts, HSBC, Société Générale (SGAM), and Winterthur, and ETFs from Barclays (iShares), Société Générale (Lyxor), and State Street (StreetTracks). We do not include Deutsche Bank (x-trackers) in our sample due to these funds' very short data history. For the Barclays iShares we show results for both the Irish and German listings. We also find multiple listings for some of the other funds (e.g., a dividend-paying fund and a capital appreciation fund), all of which we include in our final sample. Our final sample is composed of over 40 passive funds that are relevant for investors who are looking for a passive exposure to global equity markets. Because only a small number of funds have a return history that goes back to before 2003, our sample covers the period January 2003 to December 2008.

7.3 Empirical results

In this section, we investigate the impact of fund expenses and dividend withholding taxes on European passive fund performance.

7.3.1 Relative fund returns

We first analyze realized fund performances by comparing the return of passive funds and their benchmark indexes. We focus on the median 12-month return differences. We use medians to reduce the impact of the first and last data points in our sample. When we compare the performance differences for two funds, we bear in mind that these may be based on data histories with different lengths.

In Table 7.1 we summarize the realized benchmark-relative performances of the funds in our sample. The table shows that basically all passive funds underperform their benchmark. The typical underperformance ranges from 50 to 150 basis points per annum, with a median of 84 basis points. This underperformance is significantly more than the figure reported for U.S. listed passive funds. For example, Svetina and Wahal (2008) report that U.S. equity ETFs exhibit an estimated underperformance of 31 basis points with respect to the index they are tracking. Elton et al. (2002) indicate that the Standard & Poor's Depositary Receipts (SPDRs) on the S&P 500 Index exhibit a performance shortfall of 28 basis points.

Table 7.1

Performances

This table reports the performance of the passive funds in our sample measured against gross benchmark index returns. For each fund we report the median 12-month return difference measured over the January 2003 to December 2008 period.

	S&P 500 or MSCI USA	MSCI Europe	MSCI Japan or TOPIX	MSCI World	MSCI EM
ETFs					
iShares	-0.65%	0.04%	-0.45%	-0.27%	0.42%
	-1.54%	-0.60%	-0.92%	-0.76%	0.29%
Lyxor	-1.61%	-0.47%	-0.50%	-0.67%	-1.73%
StreetTracks		-0.87%			
Index funds					
Vanguard	-0.95%	-0.80%	-0.37%	-0.89%	-0.60%
			-0.32%		
State Street	-0.91%	-0.88%	-0.52%	-0.84%	
Crédit Agricole	-0.83%	-0.81%	-0.67%		
Pictet	-0.93%	-1.39%	-0.68%		-1.73%
(BNY) Mellon	-1.83%				
	-1.09%				
Coutts	-1.62%				
	-1.32%				
HSBC	-1.21%				
	-1.23%				
Société Générale	-1.31%				
Winterthur	-1.56%				
Median	*-1.23%*	*-0.81%*	*-0.51%*	*-0.76%*	*-0.60%*

If we focus on the best-performing funds, we see that for each benchmark there is at least one fund that underperforms by no more than 70 basis points per annum. We are suspicious about the few funds that seem to outperform their benchmark, as these appear to be funds with either relatively high tracking error levels or with only a small number of return observations available. We conclude that the passive funds in our sample generally earn returns that are substantially lower than their benchmark returns.

We also observe large performance differences between funds that track different benchmark indexes. The median underperformance is 123 basis points for funds that track the S&P 500 or MSCI USA Index, 81 basis points for funds that track the MSCI Europe Index, and 76 basis points for funds that track the MSCI World Index. Interestingly, the median underperformance for funds that track the MSCI Japan Index or Topix is smallest, at only 51 basis points. Funds that track the MSCI Emerging Markets Index exhibit relatively high tracking errors, as a result of which it is arguable if they truly qualify as being passive.[8] As a result, we are not surprised to find a relatively broad range of benchmark-relative performances for this group of funds. Taking into account the high tracking errors of the emerging markets funds, we do not consider their median underperformance of 60 basis points to be a particularly meaningful number.

7.3.2 Expense ratios and fund performance

Here, we investigate the extent to which the underperformance of passive funds can be attributed to their expense ratios. The expense ratios that are reported by the funds include management fees and other fees charged by the asset managers, such as share registration fees, fees payable to auditors, legal fees, and custodian fees. In Table 7.2 we summarize the reported total expense ratios of the passive funds that comprise our sample.

The lowest expense ratios reported by funds vary from 35 basis points for certain U.S. and European funds to 65 basis points for emerging markets funds.[9] The median expense ratio of the funds in our sample is 59 basis points, which implies a gap of 25 basis points with the median underperformance of 84 basis points we discuss above. This result indicates that the substantial underperformance of the passive funds cannot be attributed solely to their expense ratios. Furthermore, although there seems to be a negative relation between fund performances and expense ratios, the performance differences we observe between funds often cannot be explained by differences in their expense ratios. For example, even though the most expensive funds are also the funds with the worst performance (the BNY Mellon / Mellon fund tracking the S&P500, and the Pictet fund that

[8] We find median tracking error levels ranging from 0.5 to 0.8 percent per year for funds tracking the United States, Europe, Japan, and World indexes. In comparison, the median tracking error for funds tracking Emerging Markets is 1.5 percent per year.

[9] Hortaçsu and Syverson (2004) show that there is a wide variety in expense ratios among passive index funds tracking the S&P500 index. They develop a model in which the nonfinancial attributes of passive index funds can explain that relatively expensive funds are not competed away by the cheapest funds. Svetina and Wahal (2008) report that most new ETFs are based on indexes for which no index mutual fund exists, to avoid competition.

tracks the MSCI emerging markets index), it is not true that the cheapest funds consistently display the best performance. For example, with an expense ratio of 35 basis points per year, the Lyxor ETF tracking the S&P500, is one of the cheapest funds in our sample, but it is also among the worst-performing funds, showing an underperformance of 1.61 percent per year.

Table 7.2

Expense ratios

This table contains an overview of total expense ratios, as reported by the funds themselves. The expense ratios reported by the funds include management fees and other fees charged by the asset managers, such as share registration fees, fees payable to auditors, legal fees, and custodian fees.

	S&P 500 or MSCI USA	MSCI Europe	MSCI Japan or TOPIX	MSCI World	MSCI EM
ETFs					
iShares	0.40%	0.35%	0.59%	0.50%	0.75%
	0.40%	0.35%	0.59%	0.50%	0.75%
Lyxor	0.35%	0.35%	0.50%	0.45%	0.65%
StreetTracks		0.50%			
Index funds					
Vanguard	0.38%	0.50%	0.50%	0.50%	0.65%
			0.50%		
State Street	0.60%	0.60%	0.60%	0.60%	
Crédit Agricole	0.40%	0.40%	0.40%		
Pictet	0.76%	0.77%	0.78%		1.22%
(BNY) Mellon	1.15%				
	0.51%				
Coutts	0.85%				
	0.70%				
HSBC	1.00%				
	1.00%				
Société Générale	0.81%				
Winterthur	1.05%				
Median	*0.70%*	*0.45%*	*0.55%*	*0.50%*	*0.75%*

An even more striking observation is that the differences in performance between funds that track different benchmark indexes cannot be explained by expense ratios. Even though funds that track the major stock market indexes in the United States and Europe generally have expense ratios similar to those of funds that track the major indexes in Japan, we find that the latter funds display consistently better performance. Passive funds that track the S&P 500 or MSCI USA Indexes underperform their benchmarks by more than 120 basis points per year and funds that track the MSCI Europe underperform their benchmark by about 80 basis points per year. This figure compares to only 50 basis points for passive funds that track the MSCI Japan or Topix index.

7.3.3 Dividend taxes and fund performance

We investigate the extent to which dividend taxes may help explain the observed performance differences. We examine the taxation of dividends that are received by the funds in our sample. Dividends that are paid out by a fund may also be subjected to withholding taxes, depending on the tax status of the end-investors in the fund. However, analyzing the after-tax returns of the end-investors in a fund is beyond the scope of this paper, since our focus is on mutual fund performance evaluation. Thus, consistent with the literature on mutual fund performance evaluation, we assume that fund dividend payments are fully reinvested when calculating fund total returns.

Dividend taxes need to be considered separately because they are not incorporated in fund total expense ratios. Index providers such as MSCI have been aware of the importance of dividend withholding taxes and have acted on this by providing two types of total returns indexes. So-called *gross* return indexes assume that dividends are fully re-invested, while *net* return indexes assume that dividends are re-invested after taxation according to the worst possible withholding tax rate. Consequently, the gross return represents an upper bound on the expected return of a fund that perfectly replicates an index, while the net return represents a lower bound. Table 7.3 lists the withholding-tax rates used in the calculation of the MSCI net total return series and the average dividend yields for the most relevant regions for the funds in our analysis.

To test for the incremental explanatory power of dividend taxes over fund expense ratios, we use a regression framework in which we cross-sectionally regress relative fund performances on expense ratios, our measure of dividend taxes and, later on, a number of control variables. We present the regression results in Table 7.4.

Table 7.3

Withholding taxes and dividend yields

This table contains an overview of withholding taxes used in the calculation of the MSCI net total return series. The withholding tax rates used are the maximum rates applicable to non-resident institutional investors who do not benefit from double taxation treaties as per 2006. The table also shows dividend yields over the period January 2003 to December 2008.

	Withholding taxes	Dividend yield
United States	30%	1.9%
Japan	7%	1.3%
Europe		
United Kingdom	0%	3.5%
France	25%	3.1%
Germany	21%	2.5%
Emerging markets		
Korea	27.5%	2.0%
Taiwan	20%	3.4%
Brazil	0%	3.6%
Russia	15%	1.8%
India	0%	1.4%
China	0%	2.3%

In regression specification 1 we regress fund performances on their expense ratios. We observe a negative slope coefficient of about one, which is statistically highly significant with a t-statistic of -3.06. The adjusted R-squared value of the regression indicates that expense ratios can explain up to 17 percent of the cross-sectional variability that we find in passive fund performance. These results indicate that we can attribute a substantial portion of the variation in the performance of passively managed funds to differences in their expenses.

In regression specification 2 we regress fund performances on our measure of dividend taxes. We observe a statistically significant negative slope coefficient of 1.29 and an adjusted R-squared value of 20 percent. These results indicate that, from a statistical point of view, the explanatory power of dividend taxes as determinant of the underperformance of passive funds is at least on par with the explanatory power of expense ratios.

Table 7.4

Regression results

This table reports the results of several regressions designed to explain the cross-section of passive fund performances. The dependent variable is the median benchmark-relative performance of each fund as reported in Table 7.3. In regression specification (1) we regress fund performances on expense ratios in isolation, and in specification (2) on dividend taxes in isolation. Our main analysis consists of regression specification (3), in which we regress fund performances on expenses and dividend taxes together. Regressions (4), (5) and (6) are based on regressions (1), (2) and

	(1)		(2)		(3)		(4)		(5)		(6)	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Intercept	-0.24	(-1.10)	-0.34	(-1.99)	0.16	(0.71)	-0.37	(-0.78)	-0.69	(-2.85)	0.27	(0.59)
Expense ratio	-1.02	(-3.06)			-0.91	(-3.03)	-0.96	(-2.04)			-1.21	(-3.39)
Dividend taxes			-1.29	(-3.35)	-1.16	(-3.31)			-1.17	(-3.08)	-1.02	(-2.45)
IR							0.22	(0.84)	0.47	(2.33)	0.12	(0.52)
FR							-0.03	(-0.10)	0.27	(1.29)	-0.18	(-0.66)
GE							0.16	(0.47)	0.39	(1.48)	-0.03	(-0.10)
Adj. R-square	*17%*		*20%*		*34%*		*16%*		*26%*		*35%*	

In regression specification 3, to test for any interaction between fund expenses and dividend taxes, we run a multiple regression that contains both variables. The slope coefficients remain nearly unchanged and the explanatory power of the two-factor model increases to an impressive 34 percent. Based on the results of these regressions, we conclude that fund expense ratios and dividend taxes are distinct sources of passive fund underperformance. To get a feeling for the economic magnitude of the impact of expense ratios and dividend taxes on fund performance, we multiply the estimated slope coefficients with the average values of the expense ratios and our measure for dividend taxes. The resulting figures are -56 basis points and -48 basis points per year, respectively. This finding implies that expense ratios and dividend taxes have an economically significant and generally comparable impact on the performance of passive funds.

7.3.4 Tax efficiency

One of the most striking observations of our regression analyses is that the estimated coefficient of tax impact is very close to -1. The negative one-to-one relation between dividend withholding taxes and fund performance indicates that the typical European passive fund is unsuccessful in alleviating its tax burden. Ways in which funds could improve their tax efficiency include benefiting from tax reclaims based on international dividend tax treaties, applicable to the legal structure and the country of incorporation of the fund; or engaging in "dividend enhancement" securities lending practices; or investing in derivatives, such as total return swaps instead of physical, dividend-paying stocks. Of course, an additional requirement in this regard is that the revenues of such activities accrue primarily to the fund. If the funds were to be successful in alleviating their tax burden to some extent, then the estimated tax impact coefficient should be smaller than one in absolute terms.

The funds in our sample themselves do not report on their dividend tax efficiency. For example, the information on dividend withholding taxes in the prospectuses of the funds is typically limited to a general statement that these taxes may negatively affect fund returns and that the fund may try to mitigate the impact of these taxes, but that the fund makes no commitment whatsoever as to how this mitigated impact might affect the fund's bottom line.[10] Most funds evaluate their performance against net return indexes, indicating that investors should expect the worst with respect to dividend withholding taxes.

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[10] In theory end-investors might be able to improve their after-tax returns by reclaiming themselves some or all of the dividend withholdings experienced by their fund. In practice this is not a realistic

We also contacted several fund management companies to obtain more details on the impact of dividend taxation, but we were not able to receive clear, unambiguous feedback. In some instances we were even given contradictory information. One of the few exceptions was Deutsche Bank. This newcomer in the ETF market explicitly mentions dividend tax efficiency as one of its competitive advantages, which it achieves by investing in derivatives instead of physical stocks. In light of our findings and these recent developments, we conjecture that in coming years tax efficiency will increasingly be recognized as an important competitive advantage in the European passive fund industry.[11]

7.3.5 Listing and fund performance

We perform several follow-up regressions to test for possible interactions with fund listing. First, we construct dummy variables indicating whether the funds are listed in Luxembourg (LU), Ireland (IR), France (FR), or Germany (GE). Based on expense ratios alone, we would expect funds listed in Luxembourg to underperform funds listed in Ireland, France, and Germany, because funds in Luxembourg have an average expense ratio of 92 basis points, compared to 59, 49, and 52 for funds listed in Ireland, France and Germany, respectively. In addition to expenses, the impact of dividend taxation may also be different for funds with different listings, because, depending on their country of incorporation, funds might be able to benefit from international dividend tax treaties. However, since funds do not report on their tax reclaim activities, we do not have any a priori expectations on the possible interactions between fund listings and dividend taxes.

To investigate the extent to which performance differences between funds with different listings can be attributed to their expense ratios and our measure for dividend taxes, we augment regressions 1 to 3 with the listing dummy variables IR, FR, and GE. Regressions 4 to 6 only provide evidence of an indirect relation between fund performances and listings, resulting from differences in average expense ratios between funds with different listings. When fund expenses and listings are jointly taken into account, the explanatory power of listings disappears entirely. The results also imply that performance differences across funds with different listings are neither related to dividend taxes, nor does the explanatory power of dividend taxes change when listings are additionally taken into account.

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possibility though, as it would require a detailed, investor-specific overview of the impact of withheld dividends, which the funds do not provide.

[11] Just like capital gains tax efficiency is a known important feature for funds listed in the United States.

7.3.6 Dividend taxes and time variation in passive fund performance

We investigate if dividend taxes are also helpful in explaining variations in passive fund performance over time. If dividend taxes are indeed an important determinant of passive fund underperformance, then we would expect passive funds to display worse performance during time periods when losses due to dividend taxes are relatively high compared to periods when losses due to dividend taxes are relatively low. Time variation in the impact of dividend taxes is probable, in light of the fact that dividends tend to be distributed mainly during certain periods in the year. To formally investigate this effect, we split the sample, separately for each benchmark index, into two mutually exclusive parts. The high-tax-impact subsample consists of the months during which the return difference between the gross and net benchmark indexes is above median, and the low-tax-impact subsample comprises the months during which this difference is below the median. Table 7.5 shows the median fund performances under both regimes.

Panel A of Table 7.5 shows the return differences between gross and net benchmark indexes for both subsamples. We see that these differences can be quite substantial. For the United States, the median difference between the gross and the net return index of the S&P500 during high-tax-impact months is 76 basis points (annualized). During low-tax-impact months this figure is only 43 basis points, i.e., 34 basis points lower. This difference is 40 basis points for the MSCI Europe Index, three basis points for the major Japanese stock indexes, 25 basis points for the MSCI World Index, and 35 basis points for the MSCI Emerging Markets Index.

Panel B of Table 7.5 shows the median fund performances for both subsamples. Interestingly, we also observe substantial performance differences for the funds in the two subsamples. For example, during high-tax-impact months, passive funds that track the S&P500 or the MSCI USA display an underperformance of 114 basis points, which compares to 85 basis points during low-tax-impact months. The difference of 29 basis points is very close to the 34 basis point difference which we find at the index level. For the other regions we also note comparable differences between fund returns and index returns in the two tax-impact subsamples. These results imply significant time variation in passive fund performance that can be attributed to dividend taxes being higher in some periods than in others. Thus, the results also provide corroborating evidence for the importance of dividend taxes as a determinant of passive fund returns in general.

Table 7.5

Dividend tax regimes

This table reports the performance of the passive funds in our sample during high- and low-dividend tax regimes. For each individual benchmark index we split the sample into two mutually exclusive parts. The high-tax-regime subsample consists of the months during which the return difference between the gross and net benchmark indexes is above median, and the low-tax-regime subsample consists of the months during which this difference is below median. Panel A reports the median difference between gross and net index returns under the two regimes and Panel B reports the median benchmark-relative fund performances under each regime.

Panel A. Gross-minus-net return index

	S&P 500 or MSCI USA	MSCI Europe	MSCI Japan or TOPIX	MSCI World	MSCI EM
High dividend taxes	0.76%	0.52%	0.04%	0.57%	0.48%
Low dividend taxes	0.43%	0.11%	0.01%	0.32%	0.13%
Difference	*0.34%*	*0.40%*	*0.03%*	*0.25%*	*0.35%*

Panel B.Performance versus benchmark index

	S&P 500 or MSCI USA	MSCI Europe	MSCI Japan or TOPIX	MSCI World	MSCI EM
High dividend taxes	-1.14%	-0.98%	-0.55%	-0.93%	-1.73%
Low dividend taxes	-0.85%	-0.51%	-0.47%	-0.78%	-1.03%
Difference	*0.30%*	*0.47%*	*0.08%*	*0.15%*	*0.71%*

7.4 Conclusions and implications

In this paper we investigate the performance of index mutual funds and exchanged-traded funds listed in Europe that track the major stock market indexes for the United States, Europe, Japan, and emerging markets. Consistent with other studies, we observe considerable differences in performance between the funds, and find that expense ratios are an important determinant of relative fund performance. However, we document two notable observations that cannot be explained by differences in fund expense ratios. First, the index funds and ETFs in our sample fall short of the total returns of the benchmarks they track by substantially larger amounts than their reported expenses; and second, we observe substantial performance differences between passive funds tracking different benchmark indexes that seem unrelated to their expense ratios.

We show that these two observations are almost completely explained by the fact that fund expense ratios do not incorporate dividend taxes. Once dividend taxes are taken into account, most of the passive funds' underperformance can be explained. The explanatory power of dividend taxes as a determinant of index fund and ETF performance is at least on par with the importance of expense ratios. We find that on average, fund expense ratios contribute -56 basis points to fund performance, and that the corresponding figure for dividend taxes amounts to -48 basis points. Moreover, dividend taxes almost completely explain the differences in performance that we observe between funds that track different benchmark indexes, and also successfully explain time variation in monthly fund performances. Our results indicate that the sizeable underperformance of passive funds that track the major stock market indexes for the United States and Europe can be attributed to the impact of dividend taxation being relatively high in these regions.

Our study has several important implications. First, for a proper understanding of European fund performance, we believe it is important to realize that dividend taxes constitute a cost component with a magnitude that is, in many cases, comparable to that of the expense ratio. We conjecture that this conclusion carries over to all funds that are subject to dividend taxes, including, for example, mutual funds listed in the United States that invest outside of the United States. A brief analysis of certain U.S.-listed funds over the same sample period suggests that this is indeed the case. We find that the U.S.-listed Vanguard Index fund and the U.S.-listed Barclays iShares, both of which track the S&P 500 Index, lag the index (on a gross total return basis) by an amount which is close to their reported expense ratios, but the shortfall of the U.S.-listed Vanguard fund on MSCI Europe and the U.S.-listed iShares on MSCI EAFE is about 50 basis points larger than their expense ratios would suggest. This 50 basis point gap closely matches our measure of the impact of dividend withholding taxes, i.e., the difference between gross and net total index returns. A more thorough analysis of the impact of dividend withholding taxes on funds listed outside Europe is beyond the scope of this paper, but would constitute an interesting avenue for follow-up research that could naturally extend our results.

Second, our analysis shows that the "total expense ratio" is not, as its name suggests, a comprehensive measure of the costs incurred by a fund. Our results encourage the development of more refined measures of fund costs.

Third, our results imply that if actively managed mutual funds are evaluated against index returns that assume full reinvestment of dividends and ignore expenses, then the bar for these funds is raised too high. A more appropriate hurdle rate is the performance of passively managed funds that are available to investors in reality.

Finally, our results indicate that ignoring dividend taxes may also distort relative fund comparisons. The estimated alphas of funds that invest in regions in which the impact of dividend taxation is relatively high are underestimated if the employed benchmarks assume that dividends are fully reinvested.

8 Conclusion

8.1 Summary and implications

Inspired by the prevalence of benchmarking in academic research as well as in investment practice, we formulated three central research questions:

1. Is there alpha in the equity market, i.e. do current benchmark asset pricing models adequately describe the cross-section of stock returns?
2. Is there alpha in the asset allocation space, i.e. can active asset allocation add value over a benchmark strategic asset allocation (SAA) portfolio?
3. Can benchmark index returns actually be obtained in reality?

Below we summarize our main findings with regard to these questions and the implications of these findings.

8.1.1 Is there alpha in the equity market?

Our first central research question is whether there is alpha in the cross-section of stock returns, i.e. returns which are not explained by benchmark asset pricing models such as the Fama French 3-factor model and the Carhart 4-factor model. Three studies in this thesis relate to this question.

In chapter 2 of this thesis[1] we presented a momentum strategy which vastly improves upon traditional momentum strategies, including the benchmark momentum factor used in the Carhart 4-factor model. Our so-called residual momentum strategy exhibits risk-adjusted profits that are about double those of traditional momentum strategies. This implies that the benchmark momentum factor in the 4-factor model vastly underestimates the true potential of momentum strategies. Whereas a traditional momentum strategy is based on straight total stock returns, residual momentum is calculated by means of time-series regressions of individual stock returns on the 3-factor model. This enables us to distinguish between the part of the return that can be attributed to loadings of a stock on market beta, size and value, versus the residual (idiosyncratic) return. Our work extends previous research by Grundy and Martin (2001), who already argued that momentum strategies may be significantly improved upon by hedging out their time-

[1] This chapter is based on Blitz, Huij and Martens (2009).

varying beta exposures, but who fail to turn these insights into a feasible investment strategy.

In chapter 3 of this thesis[2] we documented a strong return irregularity which is not captured by the CAPM, 3-factor and 4-factor model. Our main finding is that stocks which exhibit a low (high) past volatility earn abnormally high (low) risk-adjusted returns subsequently. Using a risk measure that is related to volatility, namely beta, we find a similar, but less strong relation. Our work builds upon some of the earliest empirical tests of the Capital Asset Pricing Model, notably Fama and MacBeth (1973) and Black, Jensen and Scholes (1972), who were the first to document that low-beta stocks exhibit high risk-adjusted returns, and vice verse. In other words, empirically the relation between risk and return is too flat, compared to the theoretical predictions of the Capital Asset Pricing Model. Our contributions to the existing literature are to show that the anomalous relation between risk and return remains strong in recent times, is comparable in magnitude to the extensively documented value and momentum effects, is prevalent not only in the U.S. but also in Europe and Japan, and is even stronger when using simple historical volatilities instead of more sophisticated betas as the measure for risk.

In chapter 4 of this thesis[3] we critically examined recently proposed fundamental benchmark indexes and conclude that their performance is entirely explained by the classic Fama-French 3-factor model, and in particular by a large loading on the value factor within that model. Fundamental indexes, as introduced by Arnott, Hsu and Moore (2005), are defined as indexes in which stock weights are based on fundamentals instead of market capitalization, e.g. book value, sales, et cetera. According to the these authors and other proponents of fundamental indexation[4], these indexes constitute inherently superior benchmarks by having systematically less exposure to overvalued stocks and more exposure to undervalued stocks. We show that a fundamental index is, in fact, simply a new way of capturing the classic value premium. After adjusting the performance of fundamental indexes for loadings on the Fama-French value factor, their entire added value disappears. As the value premium has been known to exist for decades already, we conclude that fundamental indexation is nothing more than an active value strategy disguised as an index. Or, to put it bluntly, old wine in new bottles.

Although our third study shows that the alleged alpha of fundamental indexation is simply classic value beta, the other two studies do provide evidence of the existence of alpha opportunities in the equity market. Specifically, we find highly significant alphas for

[2] This chapter is based on Blitz and van Vliet (2007).
[3] This chapter is based on Blitz and Swinkels (2008).
[4] For example Treynor (2005) and Hsu (2006).

stocks ranked on their residual momentum and for stocks ranked on their historical volatility. These empirical findings have important implications for finance theory as well as for practitioners. Theoretically, our results challenge one of the key notions in finance, namely market efficiency. In an efficient market it should not be possible to obtain alpha based on utilizing nothing more than publicly available price information. In addition, the fact that current benchmark asset pricing models cannot explain the economically and statistically significant alphas suggests that these models are inadequate for a proper understanding of the cross-section of stock returns. Our evidence of alpha opportunities is also highly relevant for practitioners, as it indicates a way in which active management can be used to outperform the benchmark index and peer group.

8.1.2 Is there alpha in the asset allocation space?

For our second central question we shift our attention from the cross-section of stock returns to asset allocation. The essence of the question is similar though: can active asset allocation add value over a benchmark strategic asset allocation (SAA) portfolio? In practice, strategic asset allocation often turns into static asset allocation, i.e. a mix of betas that is held constant over time. As the asset allocation decision has been shown to be the main determinant of investors' end-returns, it is important to know if a more active approach towards asset allocation may provide added value.

One stream of literature shows that active asset allocation strategies may exploit effects similar to those that are known to exist within the cross-section of stock returns. For example, for equity country allocation both medium term momentum and long-term mean-reversion have been shown to be effective, see Chan et al. (2000) and Richards (1995, 1997). Another example are carry strategies for currencies, as documented by Hodrick (1987) and Froot and Thaler (1990), which may be interpreted as value strategies. In practice tactical asset allocation (TAA) strategies have become popular, which basically consist of a combination of several such strategies, implemented by means of a derivatives overlay. However, a direct comparison of a broad range of asset classes is typically not made in TAA programs, perhaps because the literature also remains largely silent on this topic.

In chapter 5 of this thesis[5] we fill this gap in the literature by examining if value and momentum effects can be observed not only within asset classes, but also across entire asset classes. Within asset classes, value and momentum effects appear to be particularly

[5] This chapter is based on Blitz and van Vliet (2008).

pervasive. For example, Asness, Moskowitz and Pederson (2009) consider the U.S. stock market, various international stock markets, the global stock market at the country level, the global bond market at the country level, currencies and commodities and conclude that within each market strong value and momentum effects are present. Our main contribution is to show that similar effects can be observed across entirely different asset classes. In particular, we document that value and momentum strategies applied to twelve key asset classes yield statistically and economically significant return premiums over the 1986 to 2007 period. For a strategy based on a simple combination of momentum and value factors we find a double digit annualized alpha. We conclude that value and momentum effects, which are known to exist within asset classes, transcend to the cross-asset level as well. However, we are not simply capturing known effects in a new way, as the combined strategy returns in particular remain strong after adjusting for implicit loadings on the Fama French value and Carhart momentum factors. Thus, although being similar in spirit, the cross-asset effects do in fact constitute different return irregularities. This adds yet another puzzle to the field of empirical asset pricing and a challenge to market efficiency.

Another stream of literature documents that variables which are related to the business cycle, such as the term spread, credit spread and dividend yield, predict time-variation in the expected return of asset classes such as equities. However, it is not obvious how these insights may be turned into a practically feasible investment strategy. Furthermore, such a strategy should not only consider the time-varying return, but also the time-varying risk characteristics of asset classes. Markov regime-switching models, which are the subject of yet another stream of literature, do explicitly identify two or more regimes which capture time-variation in the expected return, as well as risk, of an asset class. The complexity of this approach constitutes an important practical drawback though. As a result of this practitioners tend to be reluctant to rely on the predictions of Markov regime-switching models. What is lacking therefore, is an active asset allocation strategy which stabilizes risk and optimizes return over the business cycle, and which satisfies important practical criteria such as transparency and consistency with practitioner's intuition.

In chapter 6 of this thesis[6] we address this need by proposing a dynamic strategic asset allocation (DSAA) approach which stabilizes risk across the economic cycle and which has the potential to enhance expected return as well. First we show that commonly used static strategic benchmarks exhibit significant time-variation in risk and return across the business cycle. Contrary to a purely statistical approach based on Markov regime

[6] This chapter is based on Blitz and van Vliet (2009).

models, our DSAA approach is centered around a transparent economic business cycle classification model, which uses four well-known economic indicators to identify four phases in the economic cycle. As phases last about nine months on average, our proposed approach can help investors to bridge the gap between long-term SAA and short-term TAA in practice.

The DSAA philosophy and the cross-asset allocation approach outlined above can be used to extend traditional strategic and tactical asset allocation (SAA and TAA) approaches. We envisage a three-stage allocation process, where the first step consists of determining a traditional static strategic asset allocation which provides the best match with an investors' long-term objectives. An ALM study may provide the necessary insights for this. The second step consists of moving beyond the static SAA to a dynamic strategic asset allocation, based on economic regimes, with a medium-term horizon. DSAA could either be examined within the context of an ALM study or in a separate follow-up analysis. The third and final step consists of applying traditional TAA and/or novel cross-asset allocation strategies aimed at capturing short-term opportunities for enhancing return.

8.1.3 Can benchmark index returns actually be obtained in reality?

The benchmarking of active fund managers has made clear that many, in fact the majority, of active managers fail to outperform their benchmark indexes. As mentioned before, this is not particularly surprising in light of the fact that active management is a zero-sum game before costs and a negative-sum game after costs. This realization has contributed to the growing popularity of passive investing, i.e. to simply follow a benchmark index as closely as possible and at minimal costs. In many studies it is either explicitly or implicitly assumed that cheap passive exposure to (a good proxy for) the market portfolio is a realistic alternative to active investment strategies. For example, the SPDR (pronounced: spider) on the S&P 500 index has been shown to successfully replicate the index against minimal costs, see Elton et al (2002). Most of this literature concerns the U.S. market though. This brings us to our third and final central research question, namely whether it is safe to assume in general that paper indexes constitute a fair benchmark, based on the notion that an investor should be able to simply replicate the return of an index by buying and holding the index portfolio.

In chapter 7 of this thesis[7] we examine the performance of passive funds listed in Europe in comparison to their benchmark indexes. Our results show that the passive funds

[7] This chapter is based on Blitz, Huij and Swinkels (2009).

in our sample lag their benchmarks by a statistically and economically significant amount of 50-150 basis points per annum. We show that this underperformance can be explained entirely by two factors: expenses that are charged by the funds and dividend withholding taxes that are incurred by the funds. This suggests that the paper returns of standard indexes, which neither take into account expenses nor the impact of dividend withholding taxes, are not attainable for European investors in reality. In addition to robbing investors of an illusion, our results have implications for the performance evaluation of actively managed funds. As paper index returns are not always actually attainable for investors, they are not necessarily the appropriate benchmark for evaluating the performance of actively managed funds. Instead, we argue that the ultimate benchmark for active funds should be the performance which is achieved by passive funds in reality. In general this lowers the bar for active funds and, as a result, will lead to more optimistic (or at least less pessimistic) conclusions with regard to active management.

8.2 Is benchmarking itself causing distortions in asset prices?

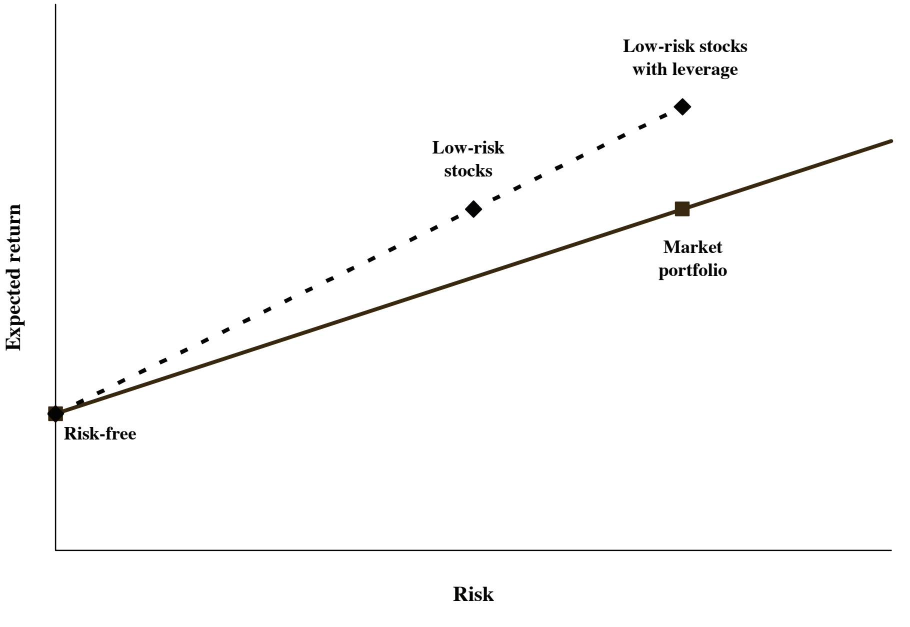
In this final section we go beyond the direct implications of our findings, by looking at the various results in this thesis with a 'helicopter view' and trying to deduce some more general insights and implications regarding the phenomenon of benchmarking. In particular, we hypothesize that it could be benchmarking itself which lies at the root of some of our key findings. In this regard we can draw a parallel with what is known in physics as the *observer effect*: changes that the act of observation will make on the phenomenon being observed. Whereas in theory benchmarking is simply the objective observation and evaluation of investor performance *ex post*, we will argue that in practice its very presence may actually be causing investors to adapt their behavior *ex ante*, with economically and statistically significant effects on asset prices. Specifically, we will link the phenomena documented in our *Volatility effect* and *Global tactical cross-asset allocation* studies to the popularity of benchmark-driven investment processes.

We first consider the volatility (or beta) effect, i.e. the finding that low-risk stocks generate high risk-adjusted returns (Chapter 3). One can wonder why this effect, which has been present for decades already, has not been arbitraged away. One reason might be that professional asset managers are typically tasked with generating a higher return than a certain benchmark, without being permitted the use of leverage. In such a setting it is very difficult to exploit the volatility effect, as empirically we find that low-risk stocks do not offer higher returns, but average returns with below-average risk. In theory it is straightforward to transform this into a portfolio with benchmark-like risk and a higher expected return, simply by taking a leveraged position in low-risk stocks. This is illustrated in Figure 8.1. However, in practice many investors are not allowed and/or reluctant to actually apply leverage, in particular on the scale needed in order to exploit the volatility effect. For example, as the risk (e.g. beta or volatility) of a low-risk stock portfolio is about one-third lower than the market level, approximately fifty percent leverage would need to be applied in order to obtain a market-like level of risk.

Figure 8.1

Graphic illustration of leveraging a portfolio of low-risk stocks

This figure conceptually illustrates how a low-risk portfolio with a market-like return can be leveraged to a portfolio with market-like risk and an above-average return.



Borrowing restrictions were already identified by Black (1972) as an argument for the relatively good performance of low beta stocks. Pure equity investors may be facing practical limitations with regard to leverage, but it is important to realize that leverage can be created relatively easily within a balanced portfolio which contains bonds and/or cash next to stocks. Black (1993) therefore suggests an increased allocation to low risk stocks as an alternative to a given allocation to the market portfolio. For example, instead of investing 50% in traditional stocks and 50% in bonds, an investor might decide to invest

70% in low risk stocks and 30% in bonds. This, however, requires that low risk stocks are included as a separate asset class in the strategic asset allocation process of investors, which is not the case in practice – at least not yet. Perhaps this will change with the recent introduction of so-called minimum variance indexes. These indexes represent portfolios that are optimized, within a set of constraints, for minimum absolute volatility, as a result of which they are highly tilted towards low-risk stocks.[8]

Interestingly, Derwall, Huij and De Zwart (2009) document that a low-risk effect is also present in the corporate bond market. Important risk factors for a corporate bond are creditworthiness and maturity. The authors find that a low-risk segment of the corporate bond market, namely short-term corporate bonds, earn abnormally high returns after accounting for all well-known risk factors. Again, restrictions on leverage may explain why benchmarked corporate bond fund managers may have little incentive to invest in securities which exhibit superior returns on an absolute risk-adjusted basis, but not necessarily so in terms of benchmark-relative returns that are not adjusted for risk. The finding that a low risk anomaly is present in more than one market strengthens our conviction that we are dealing with a real phenomenon instead of a fluke result.

A second argument for the existence of a low-risk effect is provided by Falkenstein (2009), who shifts from the usual absolute utility perspective to a relative utility perspective. Relative utility, or the phenomenon which is popularly known as "keeping up with the Joneses", is a well-known concept in economics, and previously formalized by for example Gali (1994). Falkenstein's key argument is that when agents are concerned about relative wealth, risk taking then becomes deviating from the consensus or market (benchmark) portfolio. In such a setting, all risk becomes like idiosyncratic risk in the standard asset pricing model, avoidable so unpriced. This claim is empirically backed up by numerous examples which show that standard, intuitive measures of risk, such as volatility and beta, are not positively related to returns in many asset classes and other areas of life, including movie production, sports gambling and lotteries. If we take the stock market as an example, then, according to Falkenstein's reasoning, the benchmark index represents the consensus portfolio, which minimizes relative wealth volatility. Deviating from the benchmark index by either holding low-risk stocks or high-risk stocks increases relative wealth volatility, and therefore represents diversifiable risk which should

[8] Minimum variance indexes are also subject to criticism however. For example, they require a large number of subjective assumptions and parameter choices. Furthermore, minimum variance portfolios tend to be highly concentrated. It is therefore arguable if minimum variance indexes represent passive or active investment strategies.

not require a return premium. The paper also presents a formal model highlighting the assumptions consistent with no risk premium.

The value and momentum effects which we observe at the level of entire asset classes (Chapter 5) may be caused by the same sort of behavioral biases that have been linked to these effects in the cross-section of stock returns[9], but another explanation may, again, be benchmarking. In particular, the popularity of benchmark-driven approaches for asset allocation purposes. Cross-asset allocation is in fact beyond the operating scope of most professional market participants such as fund managers and analysts, who tend to be active within one specific asset class only. For example, as U.S. high yield bond managers are typically charged with outperforming some U.S. high yield bond benchmark index, they will be mainly concerned with identifying the most attractive U.S. high yield bonds, and much less with the relative attractiveness of the entire asset class, e.g. in comparison to other asset classes such as Japanese equities and commodities. Instead, allocation decisions across asset classes tend to be made predominantly by end-investors, such as pension fund boards and private investors. Benchmark-related considerations tend to play an important role in the asset allocation process of these investors. Examples are (i) long-term considerations, e.g. adhering to a strategic benchmark which was determined based upon an asset-liability management study; (ii) fixed allocation mechanisms, e.g. the use of a pre-specified, benchmark asset mix for cash inflows (e.g. 401K plan contributions) throughout a year; and (iii) herding behavior, i.e. not wanting to deviate too much from the peer group benchmark.

Benchmark-driven approaches towards asset allocation by a large number of market participants as well as potential behavioral biases can explain why, in general, mispricings may arise at the level of entire asset classes, and why value and momentum effects can be observed in particular. A necessary condition for this situation to persist is that an insufficient amount of 'smart money' is available to arbitrage away mispricings as soon as they arise. Certain types of hedge funds might be expected to represent this 'smart money' and are thus likely candidates to take advantage of cross-asset allocation alpha opportunities in practice. When we examine the relation between our cross-market allocation alphas and hedge fund returns, a mixed picture emerges. Some results appear to be consistent, but in other cases the results are inconsistent. Thus, we conclude that

[9] The value effect has been argued to be caused by over-optimism of investors with regard to 'glamour' stocks, which are already quite expensive compared to fundamentals, and over-pessimism with regard to unexciting stocks, which are in fact relatively cheap. The momentum effect has been linked to both initial underreaction of investors to stock-price relevant news, or gradual information diffusion, and a longer-term overreaction effect, caused by investor herding. The same reasoning may explain why similar effects can be observed at the level of asset classes.

although some hedge funds may indeed be trying to exploit some of the cross-market allocation alphas that we observe, the overall results do not indicate that this is occurring at the large scale which would be needed to arbitrage away all these effects. This suggests that the value and momentum effects across asset classes are not likely to disappear overnight.

To summarize, we have argued that the popularity of benchmarking may have brought about unintended and undesirable side-effects. First, benchmarked investors may have a strong incentive to avoid investing in low-risk stocks, even when these stocks are expected to offer a superior Sharpe ratio. This happens when investors face the typical objective of generating a higher return than a given benchmark index, in the presence of constraints on the use of leverage. Second, benchmarks give rise to relative-wealth thinking, which can cause the relation between absolute risk and return to break down. Both phenomena are consistent with the empirical findings in our *Volatility effect* study. Third, benchmark-driven approaches towards asset allocation by institutional investors pave the way for macro-level inefficiencies that are consistent with the empirical findings in our *Global tactical cross-asset allocation* study.

These insights imply that benchmarking is associated with various pitfalls, which raises the question what investors should do to avoid these, or even turn the insights to their advantage. The reasoning above already contains some suggestions in this regard, such as considering low-risk stocks as a separate asset class in the strategic asset allocation process. A more radical step might be to not explicitly define a benchmark at all, in order to encourage investors to eliminate benchmark-thinking altogether from their *ex ante* investment decision making process. However, the challenge in this case is how to evaluate performance *ex post*. As soon as an explicit benchmark is introduced for performance evaluation purposes, we are effectively back to square one. Furthermore, throwing away the benchmark is essentially a sign of giving up instead of fixing the underlying problem that benchmarks may induce undesirable behavior. A better solution would therefore be to adapt benchmarks in such a way that undesirable behavior is discouraged while desirable behavior is encouraged. For example, if investors are evaluated on a risk-adjusted performance metric such as the Sharpe ratio instead of straight outperformance, they will have much more incentive to consider investing in low-risk stocks. The caveat here is that a different form of benchmarking could give rise to new inefficiencies, but the better the alignment between the benchmark and desired behavior, the smaller this problem should be. One of the most interesting directions for follow-up research to this thesis would therefore be the design of more effective benchmarking approaches. Because of its many advantages, benchmarking is not likely to disappear. The challenge, therefore, is to set and apply benchmarks in such a way that undesired side-effects are prevented.

Nederlandse samenvatting (Summary in Dutch)

Benchmarks en benchmarking vormen de rode draad die door dit proefschrift loopt. Benchmarking houdt in dat prestaties niet in absolute zin worden beoordeeld, maar relatief ten opzichte van een bepaalde vergelijkingsmaatstaf, de benchmark. Zo kunnen de prestaties van beleggingsfondsen bijvoorbeeld worden afgezet tegen die van andere, vergelijkbare fondsen, een zogenaamde peer group analyse. Aangezien alle beleggers gezamenlijk de markt vormen kan ook het marktrendement als benchmark worden genomen. In de praktijk kan hiertoe gebruik worden gemaakt van indices zoals de S&P 500 voor de Amerikaanse aandelenmarkt of de MSCI World voor aandelenmarkten wereldwijd.

In academisch onderzoek naar de Amerikaanse aandelenmarkt zijn het Fama-French 3-factor model en het Carhart 4-factor model uitgegroeid tot breed gehanteerde benchmarks. Deze modellen houden niet alleen rekening met het marktrendement, maar ook met de rendementverschillen tussen kleine aandelen ten opzichte van grote aandelen (gemeten in termen van marktkapitalisatie), waarde- versus groeiaandelen en, in het Carhart model, aandelen met een hoog momentum versus een laag momentum. Empirisch blijken deze modellen goed in staat om rendementen van uiteenlopende aandelenportefeuilles te verklaren. De eerste centrale vraag in dit proefschrift is of de Fama-French en Carhart modellen inderdaad adequate benchmarks vormen, of dat er ook rendementeffecten zijn die niet door deze modellen kunnen worden verklaard.

In hoofdstuk 2 nemen we eerst het bekende momentumeffect onder de loep. Traditionele momentumstrategieën, zoals de momentumfactor in het Carhart 4-factor model, worden gekenmerkt door een tijdsvariërend risico. Zo zullen in een stijgende markt veelal aandelen met een hoge bèta boven komen drijven, aangezien deze het meest gevoelig zijn voor het algehele marktklimaat. Door dit mechanisme worden momentumstrategieën kwetsbaar voor een draai in het marktsentiment. Het is daarom interessant om te onderzoeken of momentum ook op een zodanige wijze kan worden gedefinieerd dat geen grote systematische risico's in de strategie sluipen. De eerste stap in onze aanpak is om de tijdreeksen van rendementen van individuele aandelen eerst te regresseren op het Fama-French 3-factor model. Vervolgens construeren we een momentumstrategie op basis van de residuen van deze regressie, dus het gedeelte van de rendementen dat niet kan worden verklaard uit de gevoeligheid naar de markt, de marktkapitalisatie en de waarde/groei karakteristieken. Ons belangrijkste resultaat is dat het voor risico gecorrigeerde rendement op deze wijze verdubbelt ten opzichte van een traditionele momentumstrategie. Dit impliceert dat het momentumeffect een aanzienlijk sterker fenomeen is dan tot nu toe werd gedacht. Ons werk bouwt voort op de studie van Grundy en Martin (2001), die reeds lieten zien dat momentumstrategieën in theorie sterk verbeterd kunnen worden door eliminatie van het tijdsvariërende risico, maar die dit inzicht niet in een praktische beleggingsstrategie weten te vertalen.

In hoofdstuk 3 documenteren we een effect dat in het geheel niet wordt onderkend door de Fama-French en Carhart modellen. Ons belangrijkste empirische resultaat is dat aandelen met een lage (hoge) historische volatiliteit in de daaropvolgende periode een hoger (lager) voor risico gecorrigeerd rendement laten zien dan de theoretische modellen kunnen verklaren. Voor een risicomaatstaf die gerelateerd is aan volatiliteit, bèta, vinden we een soortgelijk effect, alhoewel de omvang van het bèta-effect wat kleiner is. Onze studie bouwt voort op onderzoek uit de jaren zeventig, waarin ook al bleek dat het voor risico gecorrigeerde rendement van aandelen met een lage (hoge) bèta onverklaarbaar hoog (laag) is. Wij laten onder meer zien dat dit effect in de daaropvolgende decennia niet is verdwenen, dat het qua omvang vergelijkbaar is met bijvoorbeeld het bekende waarde-effect en het momentumeffect en dat het fenomeen zich niet alleen voordoet in de Verenigde Staten, maar ook in Europa en Japan. Tevens geven we mogelijke verklaringen voor het bestaan van het zogenaamde 'volatiliteiteffect'. Deze verklaringen zijn geïnspireerd op de behavioral finance theorie, die koerspatronen relateert aan gedrag van beleggers, en de prikkels die zij ervaren. Als deze verklaringen inderdaad ten grondslag liggen aan het volatiliteiteffect, valt te verwachten dat het effect ook in de toekomst zal blijven bestaan.

In hoofdstuk 4 werpen we een kritische blik op recent geïntroduceerde fundamentele indices. In deze innovatieve benchmarkindices worden aandelen gewogen op basis van hun fundamentele karakteristieken, zoals boekwaarde, in plaats van op basis van hun marktkapitalisatie. De bedenkers en andere voorstanders van deze indices beweren dat dit een superieure beleggingsaanpak is, omdat op deze manier systematisch minder wordt belegd in 'overgewaardeerde' aandelen, en meer in 'ondergewaardeerde' aandelen. Wij beargumenteren echter dat fundamentele indices simpelweg inspelen op het reeds lang bekende, en uitgebreid gedocumenteerde value-effect. Ook empirisch blijkt dat het hogere rendement van fundamentele indices volledig kan worden verklaard uit overlap met het klassieke value-effect. Fundamentele indices mogen dus intuïtief aansprekend zijn, maar feitelijk doen ze weinig meer doen dan herverpakken van een reeds bekend fenomeen. Een schoolvoorbeeld van oude wijn in nieuwe zakken dus.

Voor de tweede centrale vraag in dit proefschrift verschuiven we onze aandacht van aandelenselectie naar de allocatie over complete beleggingscategorieën, zoals aandelen en obligaties. Omdat de allocatiebeslissing een grote, vaak doorslaggevende invloed heeft op het totale rendement van een portefeuille, stoppen institutionele beleggers doorgaans veel energie in het zorgvuldig vaststellen van de benchmark strategische asset allocatie. In de praktijk mondt de strategische allocatie vaak uit in een statische allocatie, waarmee beleggers mogelijkerwijs geld op tafel laten liggen. Onze onderzoeksvraag luidt daarom of actieve allocatie over beleggingscategorieën heen waarde kan toevoegen ten opzichte van een benchmark strategische asset allocatie.

In hoofdstuk 5 laten we zien dat waarde- en momentumeffecten zich ook voordoen op het niveau van de belangrijkste beleggingscategorieën. Dit vormt een aanvulling op de bestaande literatuur die reeds laat zien dat deze effecten zich voordoen binnen allerlei beleggingscategorieën afzonderlijk, of waarbij louter wordt gekeken naar voorspelbaarheid van het rendement van afzonderlijke beleggingscategorieën. Concreet vinden we dat waarde- en momentumstrategieën, toegepast op een twaalftal beleggingscategorieën over der periode van 1986 tot en met 2007, statistisch en economisch significante rendementen opleveren. Het rendement van een gecombineerde waarde/momentum strategie ligt zelfs boven de 10% op jaarbasis. De bevinding dat waarde- en momentumeffecten zich zelfs op dit niveau voordoen vormt aanvullend bewijs voor het universele karakter van deze effecten. De waarde- en momentumeffecten op het niveau van beleggingscategorieën blijken deels samen te hangen met het Fama-French waarde-effect en het Carhart momentumeffect binnen de Amerikaanse aandelenmarkt, maar bevatten daarnaast ook een unieke component. Ook voor het rationaliseren van deze bevindingen vallen we terug op verklaringen die geïnspireerd zijn op de behavioral finance theorie.

In hoofdstuk 6 beschrijven we een praktische methode voor het ontwikkelen van een zogenaamde ‘dynamische strategische asset allocatie’ strategie. Een dergelijke strategie is bedoeld om het gat tussen lange termijn strategische asset allocatie en korte termijn tactische asset allocatie op te vullen. De bestaande literatuur laat zien dat het rendement van bijv. de aandelenmarkt voorspelbaar is met behulp van variabelen zoals de helling van de yieldcurve, de risico-opslag voor bedrijfsobligaties en het dividendrendement, maar niet hoe dit in een praktische beleggingsstrategie kan worden vertaald. Andere studies laten zien dat Markov-switching modellen in staat zijn om in te spelen op tijdsvariatie in rendement en risico, maar vanwege de complexiteit zijn deze modellen in de praktijk niet heel populair. Bij onze strategie staan eenvoud en transparantie juist voorop. We laten zien hoe een dynamische strategie gebaseerd op de economische cyclus in staat is om het risico van de asset mix te stabiliseren, en bovendien het verwachte rendement te verbeteren. Daartoe ontwikkelen we eerst een transparant model voor het voorspellen van de economische cyclus, gebaseerd op vier intuïtief relevante variabelen. Vervolgens laten we zien dat een statische allocatie leidt tot een dynamisch variërend risico/rendement profiel, en hoe een dynamische allocatiestrategie tot meer stabiele resultaten kan leiden.

De derde en laatste centrale onderzoeksvraag in dit proefschrift is of de benchmarkrendementen waar in theoretische toepassingen van uit wordt gegaan in de praktijk ook daadwerkelijk haalbaar zijn voor beleggers. Veelal wordt dit impliciet aangenomen, uitgaande van de gedachte dat beleggers in de praktijk een index kunnen repliceren door simpelweg alle aandelen in die index pro rata aan te kopen. In hoofdstuk 7 van dit proefschrift nemen we de proef op de som door de performance te analyseren van passieve fondsen die in Europa aan een breed publiek worden aangeboden. We vinden dat deze fondsen tussen de 50 en 150 basispunten per jaar achterblijven bij de index die ze pogen te repliceren, wat zowel statistisch als economisch een significant gat is. Verder laten we zien dat deze underperformance geheel kan worden verklaard door twee factoren, te weten de kosten die door de fondsen worden gemaakt en het nadelige effect van dividendbelastingen. Een index die geen rekening houden met deze twee bronnen van underperformance spiegelt een rendement voor dat niet realistisch is voor beleggers in de praktijk. Dit is met name van belang bij de evaluatie van de performance van actief beheerde fondsen. Voor een eerlijke vergelijking zouden de prestaties van actieve fondsen rechtstreeks moeten worden afgezet tegen die van passieve fondsen, in plaats van tegen benchmarkindices die passieve fondsen ook niet kunnen evenaren. Dit zal leiden tot positievere, of op zijn minst minder negatieve conclusies ten aanzien van actief beleggen.

Hoofdstuk 8 bevat ten slotte een samenvatting van de belangrijkste bevindingen. Daarnaast gaan we dieper in op de mogelijke implicaties van onze bevindingen voor benchmarking in zijn algemeenheid. In het bijzonder formuleren we de hypothese dat het fenomeen benchmarking gepaard gaat met een aantal onbedoelde en ongewenste neveneffecten. We motiveren deze hypothese aan de hand van een drietal argumenten. Ten eerste introduceert beleggen ten opzichte van een benchmark de prikkel om aandelen met een hoog risico, en dus in theorie ook een hoog verwacht rendement, op te zoeken, waardoor deze aandelen te duur kunnen worden (en omgekeerd voor aandelen met een laag risico). Deze prikkel ontstaat met name wanneer beleggers de opdracht hebben om een hoger rendement te realiseren relatief ten opzichte van een bepaalde benchmarkindex, zonder dat het toegestaan is om van leverage gebruik te maken. Ten tweede leidt het gebruik van benchmarks tot het denken in termen van relatieve welvaart, waardoor de relatie tussen absoluut rendement en risico wordt verstoord. Beide fenomenen zijn in lijn met het empirische resultaat van een volatiliteitseffect in hoofdstuk 3. Ten derde kunnen institutionele beleggers marktinefficiënties creëren op het niveau van complete beleggingscategorieën, door massaal van benchmarkgedreven asset allocatieprocessen gebruik te maken. Dit is in lijn met de bevindingen in hoofdstuk 5. Het is goed mogelijk dat de voordelen van benchmarking opwegen tegen dergelijke nadelen. Desalniettemin is een interessante vraag voor vervolgonderzoek of benchmarking dusdanig ingericht kan worden dat de voordelen behouden blijven, maar ongewenste bijwerkingen voorkomen of verminderd kunnen worden.

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About the Author

David Blitz was born in Rotterdam on July 24, 1973. He attended the Christelijke Scholengemeenschap Henegouwerplein in Rotterdam, at which he obtained a VWO diploma in 1991. From 1991 to 1995 David studied at Erasmus University Rotterdam. In 1995 he completed his doctoraal in Business Econometrics with appellation *cum laude*. In August 1995 he joined the Quantitative Research department of the Institute for Research and Investment Services (IRIS), a joint-venture of Rabobank and Robeco. In 1998 this team was transferred to Robeco's asset management division. In 2000 David became responsible for coordinating the quantitative equity research efforts. A few years later, Robeco introduced its first purely quantitative equity product. By the end of the decade, this business had grown to well over 10 billion euros assets under management. In 2008 David became co-head of the Quantitative Strategies department, as it was called by then. As a spin-off of his research David has published papers in the Journal of Portfolio Management, European Financial Management, Applied Financial Economics, Journal of Asset Management, Journal of Performance Measurement and the VBA Journaal. The paper "The Volatility Effect", authored by David Blitz and Pim van Vliet, was one of the winners of the Emerald Citation of Excellence awards in 2007. David's research interests include the cross-section of stock returns, asset allocation and applied quantitative investing in general.

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BENCHMARKING BENCHMARKS

Benchmarking benchmarks is a bundle of six studies that are inspired by the prevalence of benchmarking in academic finance research as well as in investment practice. Three studies examine if current benchmark asset pricing models adequately describe the cross-section of stock returns. We present a momentum strategy based on residual stock returns that vastly improves upon traditional momentum strategies, evidence that low-volatility stocks earn abnormally high risk-adjusted returns and a critical discussion of the recently proposed “fundamental indexation” approach. Two studies examine whether active asset allocation can add value over a benchmark strategic asset allocation (SAA) portfolio. We empirically find that value and momentum effects do not only exist within, but also across asset classes, and we present a practical framework for dynamic strategic asset allocation based on the business cycle. The final study examines whether benchmark index returns can actually be obtained in reality. We find that passive funds listed in Europe lag their benchmarks by a statistically and economically significant amount of 50-150 basis points per annum, as a result of expenses and dividend taxes. Based on the overall results we hypothesize that the phenomenon of benchmarking itself may lie at the root of some of our key findings and that the challenge is to adapt benchmarks in such a way that desired behavior is better encouraged.

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Erasmus Research Institute of Management - **ERIM**
Rotterdam School of Management (RSM)
Erasmus School of Economics (ESE)
P.O. Box 1738, 3000 DR Rotterdam
The Netherlands

Tel. +31 10 408 11 82
Fax +31 10 408 96 40
E-mail info@erim.eur.nl
Internet www.erim.eur.nl

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