MSc. Thesis
Master in Finance and Investments

Performance Evaluation of Actively Managed Mutual Funds

• With Focus on Active Share

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Abstract

This thesis uses two measures of active fund management, active share and tracking error, to evaluate whether the performance of actively managed mutual funds is related to the level of active management. By combining active share and tracking error, a methodology introduced by Cremers and Petajisto (2009), it is possible to sort active funds into five fund groups of active management, namely: i) Closet Index funds, ii) Factor Betting funds, iii) Moderately Active funds, iv) Concentrated funds, and v) Stock Picking funds.

Based on a sample of 2,182 actively managed mutual funds with eight different investment areas in the period 02/28/1994 - 05/31/2015, it is found that the level of active management does matter in terms of performance. The performance evaluation on the total sampled funds showed that Closet index funds and Stock picking funds generated a superior benchmark-adjusted return before adjusting for fees, while the results were insignificant after fees. In order evaluate the performance of the sampled funds more accurately to account for potential different market characteristics, the funds have been further sorted according to specific investment areas. In this evaluation, the relationship between benchmark-adjusted performance and level of active management in the eight markets turned out to be ambiguous. Some of the highlights were that less actively managed funds, i.e. Closet Index funds, consistently underperformed their benchmark after adjusting for fees, whereas highly actively managed funds, i.e. Concentrated funds and Stock Picking funds, consistently outperformed their benchmarks before fees, while there was no statistical support after fees.
In conclusion, as fund performance in practice is based on returns after fees, the thesis does not provide evidence that the two active measures, active share and tracking error in combination, can be used to identify high performing funds. Though, some of the findings suggest that the two active measures may be used to identify less actively managed funds that in some markets consistently underperform net of fees.
Furthermore, it is found that the two measures, in particular active share, may have limitations in regards to the number of stocks held by the fund and markets with certain characteristics in terms of benchmark size. Consequently, evaluations of funds in small markets or funds with many stocks may be subject to a wrongly determined level of active management. The thesis suggests that practitioners going forward should take such circumstances into account by evaluating the level of active management based on a benchmark specific simulated mean active share rather than the industry standard threshold of 60% set by Petajisto (2013) for the US market.

Preface

This is a final dissertation thesis for receiving a MSc. degree in Finance and Investments at Copenhagen Business School. I wish to thank Senior Vice President at Tryg Investments, Kenneth Lillelund Winther, for his supervision and thoughtful inputs. Additionally, I wish to thank two of my former colleagues at Morningstar Inc., Client Solutions Consultant, Jens Nielsen, and Chief Financial Analyst, Nikolaj Mikkelsen for providing data.

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Contents

CHAPTER 1

Introduction

Active management refers to a portfolio management strategy, where the portfolio manager makes selected specific investments in assets with the purpose of outperforming the market and so-called investment benchmarks. The passive investment strategy however, refers to investors replicating the investment weighting of a benchmark index, typically through index funds, with the expectation of a similar risk and return. For decades, the active management strategy has been a core part- and a significant revenue contributor for wealth management firms and divisions in banks in all parts of the world[1]. Measured on assets under management, the global actively managed equity mutual fund industry is significantly larger than the passively managed fund industry, being estimated to manage more than USD 23 trillion versus approximately USD 6 trillion in 2016, respectively[1].

While the active management fund industry is of significant size and clearly demanded by private and professional investors, the strategy has also been- and is still subject to a wide range of criticism. Traditional financial theory states that markets are efficient and that one cannot outperform them consistently through an active strategy. Furthermore, comprehensive studies on historical performance of actively managed funds tend to show that they fail to beat the passively managed funds. Meanwhile, active managers succeed at requiring significantly higher management fees for their service than charged by passively managed funds.

However, over the past years, some academicians and advocates of the active management strategy have claimed there is more to it when it comes to evaluating the historical performance of the two strategies. Newer studies show that the level of active management varies significantly between actively managed funds and that evaluating a group consisting of funds with low- and high level of activity is likely to bias the result. Instead, they suggest the evaluation of performance is more accurate and conclusive if one distinguishes between less, medium and highly actively managed funds.

In 2009, professor in finance and current portfolio manager at BlackRock, Antti Petajisto and professor in finance at University of Notre Dame, K.J Martijn Cremers, conjointly introduced a new and since widely recognized methodology to determine the so-called 'active'. The methodology determines the level of active management

[1]Source: Morningstar Direct, Figure A.1, Appendix A.

of the evaluated funds and categorizes them into homogenous groups based on two measures: active share and tracking error. This, ultimately allows for a more accurate performance evaluation of the relationship between high fund performance and level of active management. The approach works with five groups, namely: i) Closet Index funds, ii) Factor Betting funds, iii) Moderately Active funds, iv) Concentrated funds, and v) Stock Picking funds.

Based on the above, I have been motivated to work on the following problem statement.

1.1 Problem Statement

- To what degree can the two active measures be used to determine the relationship between high fund performance and the level of active management?

In order to answer the main problem statement, the below five sub-questions will be assessed:

a What are the implications for applying the active share measure for funds and benchmarks with different characteristics?

b What are the characteristics of funds with high active share?

c To what degree are the sampled funds actively managed?

d What is the performance of the different groups of active management in the examined markets?

e What are the factors/variables explaining benchmark-adjusted fund returns across the different groups of active management?

The five sub-questions will be assessed on the basis of 2,182 sampled actively managed funds in the period 28/02/1994 - 31/05/2015.

1.2 Delimitation

Based on the main problem statement and the five sub-questions, the scope of this thesis can be narrowed down to two main objectives. 1) to examine the level of active management of the sampled funds using the two active measures, active share and tracking error, and 2) to evaluate the performance of the sampled funds with different level of active management. As opposed to tracking error, active share has received much attention since its publication. The thesis primarily seeks to conduct an in-depth analysis of active share, and only briefly analyze tracking error. For simplification purposes, the thesis take the perspective of a private investor and only

evaluates actively managed retail equity funds. This means that the sample has been delimited from institutional funds, fixed-income funds, funds of funds, blend funds, and index funds. Additionally, underlying share classes of the corresponding mother fund have also been excluded due to that the majority of funds have an identical track record and only deviate in its traded currency[2].
In terms of the performance evaluation, the minimum cut-off point for number of monthly observations has been set to six, which serves to exclude funds without matching monthly returns and portfolio holdings of a minimum of six months.
When conducting the performance evaluation, both gross and net risk-adjusted returns are calculated using Jensen's alpha and Carhart's four-factor model. Both gross and net returns are benchmark-adjusted, which is equivalent to the fund's excess return of the benchmark. The net returns only account for ongoing expenses and does not include of other related fees such as front-end loads, deferred loads, redemption fees and performance fees. Finally, I have delimited the performance evaluation from including Fama and French's new five-factor model published in 2014.

It should be noted that the Morningstar Direct[3] database is the primary source of data, which has been implemented and analyzed through the statistical software program R. Brief parts of the R-code can be found in Appendix E, whereas all lines of R-code along with data files can be found at `https://drive.google.com/drive/u/0/folders/0B0aaEVAK-QTCV0ox0ExZZEUxS1E`

[2]However, I acknowledge that some share classes can have different fee structure depending on which country the fund is domiciled in, and can ultimately make the share classes deviate from one another.

[3]A licensed product by Morningstar Inc.

CHAPTER 2
Theoretical Background

This chapter consists of two main sections: section 2.1) Literature Overview; Description of previous related studies, and section 2.2) Theory; Description of relevant theories that the thesis is based on.

2.1 Literature Overview

The following presents the most relevant studies for the problem statement. The section is divided into four subsections, where each deals with different types of studies: 2.1.1) Studies on funds with different levels of active management. 2.1.2) Risk-adjusted performance evaluation studies. 2.1.3) Studies on persistence in fund performance. 2.1.4) Studies on fund-specific variables' relation to fund performance.

2.1.1 Studies on Funds with Different Levels of Active Management

Since Petajisto and Cremers (2009) first introduced active share (AS) and their new methodology of combining active share and tracking error (TE) for measuring funds' level of active management, AS has received wide attention both from academicians and practitioners. Particularly, investment management firms have shown great interest in the AS measure and have as a result attributed to a significant part of the published papers. Table 2.1 illustrates a time line of the most recognized papers on the subject.

In 2009, Petajisto and Cremers conducted a performance evaluation of 2,647 US domiciled equity funds in the period 1980-2003. As opposed to other performance studies in the literature, their study sorted active funds into different levels of active management based on AS an TE in combination. The study showed that funds with high levels of active management significantly outperformed their benchmarks both before and after fees. Conversely, they also found that funds with low levels of active management significantly underperformed their benchmarks after fees. These results were, at the time, considered unique in the literature, which led to multiple papers applying the same methodology for evaluating performance on actively managed mutual funds.

Table 2.1: Time line of the most recognized studies on combining active share and tracking error

Aug 2009	Petajisto and Cremers introduce AS and propose to apply the measure in conjunction with TE to distinguish between active funds' level of active management. They conclude a relationship between high level of active management and high fund performance.
May 2012	Vanguard examines similar relationship but find no evidence of highly actively managed funds being correlated with high performance.
Jan 2013	Petajisto conducts a similar study with a different sample period and find consistent results with the original 2009 study.
Mar 2013	Lazard Asset Management extends the sample to include international funds, and also find consistent results for US funds with the original 2009 study.
Feb 2014	Fidelity Investments examines the two measures as a proxy for high performance, and find no such use.
Apr 2015	AQR Capital Management provides the perhaps most critical study to date, which states that AS has no empirical nor intuitive correlation with performance.
Jun 2015	The study by AQR Capital Management results in two separate responses from the authors themselves, Petajisto and Cremers, arguing against the conclusions made by AQR.
Mar 2016	Morningstar examines AS in European equity funds and finds no clear evidence of high levels of active management being associated with high performance.

Source: own contribution

A few years later, one of the world largest investment management firms and perhaps the biggest advocate of passive management, Vanguard[1], conducted a similar study and found no relationship between funds with high level of active management and high performance. The study from Vanguard also questioned the causality between AS and performance and alluded that the level of active management should be accompanied with manager skill.

In 2013, one of the co-authors, Petajisto, published an updated study with an extended sample period spanning from 1980-2009, including fund performance data

[1] Written by Todd Schlanger, Christopher B. Philips, and Karin Peterson Labarge[2].

from the financial crisis[2]. This study concluded similar findings as to their initial study, i.e. funds with high levels of active management tend to outperform their benchmark, even when markets are volatile. Conversely, funds with low levels of active management underperformed their benchmarks after fees.

Later in 2013, Lazard Asset Management[3] contributed to the active management debate by conducting a study of international equity funds using the methodology of Cremers and Petajisto (2009). The study concluded similar findings to Cremers and Petajisto (2009) and Petajisto (2013) for US domestic funds. The study by Lazard Asset Management further investigated AS and stressed that the characteristics of funds' benchmark is of great importance in order to accurately interpret the AS measure.

In 2014, another large investment management firm, Fidelity Investments[4], published a study also using the same methodology as Petajisto and Cremers (2009) and Petajisto (2013). The study by Fidelity Investments concluded that AS does not serve as a proxy for high performance. Moreover, the study linked funds with high AS to be associated with higher return dispersion and thus a higher downside risk.

In 2015, AQR Capital Management[5] (AQR) published their study on whether the two measures, AS and TE, explain fund performance using similar methodology and identical data as in the studies of Petajisto and Cremers (2009) and Petajisto (2013). As opposed to both studies from Petajisto and Cremers, AQR found no evidence between the level of active management and high performance. Additionally, the authors behind the study of AQR specifically criticized the theoretical basis for such relationship. Later in 2015, this criticism was followed up by Petajisto and Cremers them selves through a seperate respons to the study made by AQR[6][6][7].

In 2016, the independent research firm, Morningstar published the latest study, which opposed to the majority of studies on the subject, examines European equity mutual funds. The study by Morningstar[7] showed no clear evidence of highly actively managed funds European funds being associated with high performance.

To sum up, the consensus among the findings of the studies examining whether funds' level of active management are related to high performance is somewhat ambiguous. Most of the studies are conducted on US equity funds, whereas only Lazard Asset

[2] And a slightly different methodology.

[3] Written by Erianna Khusainova and Juan Mier (originally publsihed in 2013, revised and republished in 2014)[3].

[4] Written by Tim Cohen, Brian Leite, Darby Nielson, and Andy Browder[4].

[5] Written by Andrea Frazzini, Jacques Friedman, and Lakasz Pomorski[5].

[6] In their respons to AQR, there were arguments related to the intuition and causality behind the relationship between funds with high AS and high performance, as well as arguments about the applied methodology.

[7] Written by Mathieau Caquineau, Matias Mottola, and Jeffrey Schumacher[8].

Management and recently Morningstar provide some evidence of funds investing outside the US. Thus, this makes an interesting case to examine funds across different markets further.

2.1.2 Risk-adjusted Performance Evaluation Studies

Finding actively managed funds that outperform their benchmarks on a risk-adjusted basis has frequently been examined in the literature. One of the first and most recognizable studies on risk-adjusted performance was performed by Michael C. Jensen in 1967. With inspiration from the Capital Asset Pricing Model (CAPM), Jensen introduced the model, 'Jensen's alpha' for the purpose of determining whether mutual funds with different risks, i.e. sensitivity to the market, were able to generate abnormal returns on average. Based on a sample of 115 actively managed mutual funds in the period 1945-1964, Jensen found that none of the funds were able to consistently outperform their benchmark before and after accounting for fees[9].

In 1992, Fama and French argued that the traditional CAPM with the market portfolio being the only factor did not fully capture assets' exposure to systematic risk. Based on this argument, Fama and French (1992) introduced the three-factor model as an empirical extension of the CAPM. As opposed to the CAPM, the three-factor model included two additional risk factors: size and book-to-market value. While Fama and French in their 1992 study did not directly examine mutual fund performance, they found empirical evidence that the two risk factors were proxies for market anomalies. The logic for including size as a risk factor was based on findings, which suggested that smallcap stocks on average outperformed largecap stocks. The explanation for this relationship has to do with small firm prospect's being more sensitive on average compared to larger firms, which ultimately is compensated for by a higher expected return[8][10]. The logic for including book-to-market was also based on findings, which indicated that stocks with low growth prospects, i.e. high book-to-market value, on average outperformed stocks with high growth prospects. The intuition for this relationship is that firms with high growth prospects are more likely to experience an overreaction by the market compared to firms with low prospects (ibid.). Empirically, the two risk factors are proven to increase the explanatory power of variation in stock returns[11]. The three-factor model is given by Fama and French (1992) as,

$$R_{it} - r_t = \alpha_i + \beta_{1i}(R_{mt} - r_t) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \epsilon_{it} \tag{2.1}$$

Where, R_{it} and r_t represent the return on fund/stock i, and the risk free rate, respectively. R_{mt} is the market return, SMB_t is the return of a portfolio containing smallcap stocks minus the return on largecap stocks, and HML_t is the return of a portfolio containing stocks with high book-to-market value minus the return on stocks

[8] All other things held constant, a small firm is more likely to default than a large firm.

with low book-to-market value. β_{1i}, β_{2i}, β_{3i} are estimates capturing one of each factor's variation in expected returns[12]. α_i is the model intercept for fund/stock i, and ϵ_{it} represents the error term[13]. While the three-factor model is considered an appropriate model for explaining the variation in returns, a more comprehensive model for evaluating risk-adjusted performance is given by Carhart (1997) and is further described in subsection 2.1.3.

After much dispute about the three-factor model by Novy-Marx (2012), and Titman el al. (2004) Fama and French published a new five-factor model in 2014[9], adding two new factors to their original model: profitability and investment. The two factors are proxies for stock's operating profitability and growth in book equity, respectively. Much in line with the book-to-market factor, the logic for including profitability is that stocks with high operating profitability on average tend to outperform stocks with low operating profitability. The logic for including the investment factor is that stocks with low expected growth in book equity tend to outperform stocks with high expected growth in book equity[12]. The five-factor model is given by Fama and French (2014) as,

$$R_{it} - r_t = \alpha_i + \beta_{1i}(R_{mt} - r_t) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \beta_{4i}RMW_t + \beta_{5i}CMA_t + \epsilon_{it} \tag{2.2}$$

Where, RMW_t is a portfolio containing stocks with strong profitability minus the return on stocks with poor profitability, and CMA_t is a portfolio containing stocks with high investment minus the return on stocks with low investment. In their new five-factor model, Fama and French discovered an significant improved variation in expected returns (ibid.). However, as the five-factor model is a relatively new proposal, the literature is still digesting whether the model is considered to be more comprehensive in explaining the variation in returns than Fama and French's (1992) three-factor model and Carhart's (1997) four-factor model.

2.1.3 Studies on Persistence in Fund Performance

While several studies have investigated whether certain funds have generated abnormal returns, a smaller fraction of studies examines if the fund performance is persistent over time. For studies related to fund performance persistence, the perhaps most prominent research is conducted on US funds by Carhart (1997), whereas Quigley and Sinquefield (1999) also provide a widely recognized study on performance persistence of UK funds[10].

Based on Fama an French's (1992) three-factor model, Carhart's (1997) examines the performance persistence of 1,892 US funds by adding a fourth momentum factor

[9] In their working paper drafted September[12].

[10] Other studies on performance persistence include Wermers (1996), and Chen, Jegadeesh and Wermers (2000)[10].

(known as Carhart's four-factor model, eq. 2.9). The momentum factor works as a proxy for performance persistence and is constructed by a portfolio of fund returns, which are ranked into deciles based on their previous monthly returns (on a rolling basis)[11]. Carhart finds that there exists a persistent significant negative alpha among the deciles with the poorest performance, whereas no significant persistent positive alpha among the top performing deciles[14][10].

Another performance persistence study from Quigley and Sinquefield (1999) evaluated 752 UK unit trusts in the period 1978-1997 (identical to OE mutual funds). As to Carhart (1997) they ranked the sampled funds into deciles based on every 12 month of returns, on a rolling basis, and found an annual spread of 3.54% between the highest and lowest performing decile. However, similar to Carhart's findings in 1997, only the returns of the lowest deciles were found to be statistically significant at a 5% level, while the returns of the higher deciles were insigificant[10]. The spread indicated that if an investor were to follow a strategy of buying the portfolio of funds in the highest decile and simultaneously sellling the portfolio of funds in the lowest decile, it would generate an annual abnormal return of 3.54%. This strategy may seem promising in theory, but would involve considerable buying and selling in practice, i.e. a high portfolio turnover, which would drive up the transaction costs and limit the excess return after fees[10].

The consensus in studies on persistence in mutual fund performance is that there is statistical evidence for funds that persistently tend to underperform their benchmark over time. On the contrary, there is no clear statistical support on whether high performing funds are able to uphold the high performance over time.

2.1.4 Studies on Fund-specific Variables' Relation to Performance

In the search of high performing funds, several studies examine whether various fund-specific variables have a relation to fund performance. Some of the more commonly examined fund-specific variables in the literature are: fund size, fund fees, manager tenure, and portfolio turnover.

In an extensive cross-country study of 10,568 sampled funds in the period 1999-2005, Ferreira et al. (2007) examined the relationship between high fund performance and a series of fund-specific variables such as fund fees, manager tenure, and fund size. In terms of fund fees, the study revealed that higher annual fees and initial charges (e.g. front-end load) are positively related to performance. The relationship suggests that active fund managers are worth their excess fees. Additionally, the study revealed that manager tenure for funds that are managed by a single portfolio manager tend to outperform team-managed funds. This suggests that the additional costs associ-

[11]This methodology enables one to distinguish between funds, which are persistently performing well and poor.

ated with having multiple portfolio managers is not justified in terms of returns. In regards to fund size, the study found that large funds tend to perform better than the average sized fund[15]. This may be due to economies of scale, where a fund's costs are likely to be fixed and thus not dependent on a fund increasing its size.

Others studies have found opposing relationships for the specific variables. For example Chen et al. (2004) find that fund performance erodes with fund size[12]. This relationship can be explained by fund size being closely related to liquidity, which particularly makes it unfavorable for large funds to invest in markets containing small-cap stocks[16]. In terms of manager tenure, the study finds a similar relationship to Ferreira et al. (2007), when investigating the effect of a fund being managed by a single portfolio manager as opposed to a team-managed fund[17].

A third study by Sheng-Ching Wu (2014) examines the relationship between portfolio turnover and mutual fund performance. The study revealed a negative relationship and can be explained by a high portfolio turnover being associated with high trading costs, which diminish the net returns.

In sum, the literature provides unclear findings on whether a certain fund-specific variable can help identify funds with high performance.

2.2 Theory

This section covers the most relevant theories for this thesis. The section is divided into four subsections: 2.2.1) The capital asset pricing model; Description of the CAPM. 2.2.2) Efficient market hypothesis; Description of the different forms of EMH. 2.2.3) Performance measures; Description of Jensen's alpha and Carhart's four-factor model. 2.2.4) Measures of active management; Description of AS and TE.

2.2.1 The Capital Asset Pricing Model

With groundwork made by Harry Markowitz and later developed by William Sharpe (1964)[13], the Capital Asset Princing Model (CAPM) plays a central role in modern portfolio theory. Under a set of assumptions, the CAPM describes the expected return of any given risky asset offered in the market. The CAPM is given by,

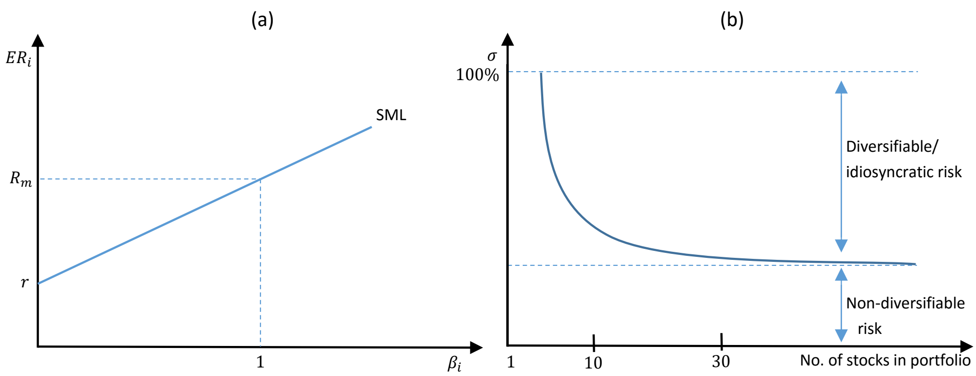
$$ER_i = r + \beta_i(ER_m - r) \tag{2.3}$$

[12] Whereas the relationship between fund performance and fund family size is found to be insignificant.

[13] John Lintner (1965), and Jan Mossin (1966) also contributed to the development of the CAPM.

Where, ER_i is the expected return on asset i, r is the risk-free rate, ER_m is the return on the market, and β_i is asset i's sensitivity with respect to the market[14][11][10]. The CAPM expresses the expected return-beta relationship, which is set to hold for all investable assets. In the CAPM, the sum of all assets represents the market portfolio which equals a beta of 1. Thus, the CAPM provides an asset's sensitivity to the market portfolio, where a beta above or below 1 is considered aggressive or defensive, respectively. Eq. 2.3 is also frequently presented as the Security Market Line (SML), where the slope is $ER_m - r$, shown in Figure 2.1 part (a). According to the CAPM assumptions (described below), all individual assets in the market are fairly priced and must be lying on the SML. In other words, the CAPM assumes stock prices are mostly in a state of equilibrium, hence any alpha would invite investors to exploit the arbitrage opportunity until the mispriced asset is fairly priced. If an asset was to be over- or underpriced, i.e. negative or positive alpha, it would result in the asset being either below or above the SML (ibid.). The SML can also be viewed from the perspective of an investor. For instance, a risk-taker would presumably choose assets which lie above the market portfolio on the SML, and thus be compensated for the excess risk taken with higher expected returns (vice versa with a risk-averse investor).

Figure 2.1: The Security Market Line and the diversification effect



Note: Graph (a) illustrates the Security Market Line, graph (b) illustrates the diversification effect.

Source:* *own contribution (inspiration from Cuthbertson and Nitzsche, 2004)

The following lists the assumptions of the CAPM;

[14]Beta is formally given by,

$$\beta_i = \frac{Cov(R_i, R_m)}{Var(R_m)} \tag{2.4}$$

1. Investors are mean-variance optimizers, i.e. investors are assumed to be rational.
2. Investors have homogeneous expectations, i.e. identical inputs.
3. Investors have a planning horizon of a single period.
4. Investors can trade all assets publicly at fair market prices. Moreover, investors are allowed to initiate short positions by lending at the risk-free rate. Lastly, it is assumed that no transactions cost nor taxes are present (ibid.).

While the CAPM provides a simplified and an intuitive interpretation of the relationship between expected return and risk for any given asset, it has been criticized when estimating the model empirically. One of the critiques, pointed out by Roll (1977), is the validity of the market portfolio. Often when applying CAPM in practice, a broad stock index such as the S&P 500 serves as a proxy for the market portfolio. Using S&P 500 only including stocks contradicts with the CAPM assumption of a true market portfolio including all investable assets, e.g. bonds, commodities, etc.[18][10]. A similar criticism pointed out by Fama and French (1993) is the market beta's lack of ability to explain cross-section variability. In theory, the CAPM states that all assets in the market should fall on a 45 degree line, empirically however, this is not the case. When sorting funds into 25 different portfolios based on size and value, Fama and French (1993) found that US stocks' beta tend to range from 0.8 to 1.5[10]. Thus, while the CAPM in theory is an intuitive model to explain the relationship between assets' expected return and the sensitivity to systematic risk, it is not necessarily an accurate model in practice.

2.2.1.1 The Power of Diversification

One of the, perhaps, only free lunches in finance is the power of diversification. By pooling a sufficient number of uncorrelated assets in a portfolio, one can reduce the idiosyncratic risk (firm-specific risk) of a portfolio. The risk of a portfolio with n assets is given by,

$$\sigma_p^2 = \sum_{i=1}^{n} w_i^2 \sigma_i^2 + \sum_{i=1}^{n} \sum_{\substack{j=1 \\ i \neq j}}^{n} w_i w_j \rho_{ij} \sigma_i \sigma_j \tag{2.5}$$

Where, w_i is the proportion held in asset i, σ_i^2 is the variance of asset i, and ρ_{ij} is the correlation between the assets of the portfolio[10].
From eq. 2.5 it becomes apparent that ρ_{ij} has an impact of the variance and thus the risk of the overall portfolio. The following provide an example by Cuthbertson and Nitzsche (2004), which simplifies how diversification can minimize a portfolio's

idiosyncratic risk. First the correlation between all assets in the portfolio is set equal to zero, $\rho_{ij} = 0$. The variance of a portfolio of n assets then becomes,

$$\sigma_p^2 = (w_1^2\sigma_1^2 + w_2^2\sigma_2^2 + ... + w_n^2\sigma_n^2) \tag{2.6}$$

Secondly, the proportions of asset in the portfolio are set to be equally weighted, i.e. $1/n$, and variances of the assets are set to equal each other, $\sigma_i^2 = \sigma^2$. This gives,

$$\sigma_p^2 = \frac{1}{n^2}n\sigma^2 = \frac{1}{n}\sigma^2 \tag{2.7}$$

Eq. 2.7 shows when an increasing number of uncorrelated assets are pooled, i.e. n $\rightarrow \infty$, the variance of the portfolio goes to zero (ibid.). The logic behind this relationship is that, when holding uncorrelated assets their idiosyncratic risk on average offsets each other. Thus, holding many assets, preferably uncorrelated, will minimize the risk of the overall portfolio. This is illustrated in Figure 2.1 part (b). The Figure shows that an investor can reduce the idiosyncratic risk by adding stocks to the investor's portfolio whereas the systematic risk remains fixed as it is independent of the number of stocks added. Cuthbertson and Nitzche (2004) have shown that one in practice can minimize the portfolio risk significantly by randomly adding a large number of stocks, even if the returns of the stocks are somewhat correlated. For example, when increasing the number of stocks held from one to ten, the portfolio variance falls rapidly, whereas the portfolio variance stabilizes after adding 30 randomly selected stocks to the portfolio (also shown in Figure 2.1 part (b)).

2.2.2 The Efficient Market Hypothesis

When evaluating the performance of actively managed mutual funds, the perhaps biggest advocate against active portfolio management is the Efficient Market Hypothesis (EMH). Similar to CAPM, the EMH assumes the market to be efficient, implying that it is impossible to sustain a positive alpha over time. More specifically, the EMH states that stock prices are reflected by all the available information circling in the market, which means that only new information can cause prices to change. According to Bodie et al. (2014), the EMH is based on the allegation that movement in stock prices follow a random walk, i.e. all stocks have unpredictable price patterns. This implies that no fund manager or investor should conduct analysis to find mispriced securities[11][19].

There exists three different versions of the EMH: the weak-form, semistrong-form and the strong-form. All the three versions to a certain degree postulates that the stock market is efficient. The weak-form states that it is impossible to consistently generate abnormal returns by trading on historical prices or momentum effects. Thus, the weak-form disprove the possibility of technical analysis being a profitable trading strategy. The semistrong-form is more strict in terms of market efficiency than the weak-from, and assumes that information beyond historical prices such as data used for fundamental analysis is not a profitable trading strategy. The strong-form assumes the highest degree of efficiency and states that it is impossible to consistently generate abnormal returns, even for insiders such as executives trading their own stock (ibid.). Of the three versions of EMH, the most realistic form in practice is arguably the semistrong-form.

2.2.3 Performance Measures

When evaluating fund performance an appropriate risk-adjusted performance measure is required due to funds' different risk levels. While there are numerous ways to determine if a fund has produced a superior risk-adjusted return, two of the most commonly used models remains to be Jensen's (1968) alpha and the Carhart's (1997) four-factor model[15][11][10].

2.2.3.1 Jensen's Alpha

Jensen's alpha is given by the following linear regression equation,

$$R_{it} - r_t = \alpha_i + \beta_i(R_{mt} - r_t) + \epsilon_{it} \tag{2.8}$$

Where R_{it} is the return of fund i at time t, r_t is the risk-free rate at time t, and R_{mt} is the market return. β_i is the slope coefficient, which is an estimate of asset i's sensitivity to the market, and α_i is the model intercept. Lastly, ϵ_{it} is interpreted as the error term of fund i at time t.
It is noted that, a positive (or negative) statistically significant estimate of the intercept, i.e. $\alpha > 0$ (or $\alpha < 0$) indicates an average superior (or inferior) risk-adjusted performance of the fund. If $\alpha = 0$, Jensen's alpha becomes the CAPM, eq. 2.3. It is also noted that Jensen's alpha assumes CAPM to be an appropriate measure of equilibrium returns, which in theory means that any fund should lie on the SML. The exact point on the SML is determined by the riskiness of the fund's holdings[10].

2.2.3.2 Carhart's Four-factor Model

While the market portfolio in Jensen's alpha is considered a good model for measuring performance, empirical findings show that when the model is extended to include additional factors such as size, book-to-market value and momentum the model will improve the explanatory power[13][14]. Carhart's four-factor model is given by the following regression equation,

$$R_{it} - r_t = \alpha_i + \beta_{1i}(R_{mt} - r_t) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \beta_{4i}MOM_t + \epsilon_{it} \tag{2.9}$$

[15] Ferson and Schadt (1996) propose to use conditional performance measures, which takes changing market conditions into account[10]. However, in this thesis unconditional versions of Jensen's alpa and Carhart's four-factor model are applied.

Where, SMB_t, HML_t, MOM_t are portfolios that mimics small minus big, high minus low, and momentum risk factors[16]. The small minus big-factor measures the difference between returns on smallcap stocks vs. largecap stocks. The high minus low-factor measures the difference between returns on high book-to-market value stocks vs. low book-to-market value stocks. The momentum-factor measures the difference in returns between previously high performing stocks vs. previously poor performing stocks[10].

2.2.4 Measures of Active Management

Active management is defined by Petajisto and Cremers (2009) as the opposite of passive management. A zero deviation from the benchmark indicates a fund pursuing a passive management strategy, whereas any deviation from the benchmark would define an active fund pursuing an active management strategy. While it is relatively easy to identify funds that deviate from the benchmark, it is more challenging to define to which level the fund is deviating or so called actively managed.
In the literature the two most commonly used measures for determining a fund's level of active management is AS and TE.
AS is introduced by Cremers and Petajisto (2009) as the percentage of a fund's portfolio weights that differentiates from the fund's chosen benchmark weights and is given by,

$$ActiveShare = \frac{1}{2} \sum_{i=1}^{N} |w_{fund,i} - w_{benchmark,i}| \tag{2.10}$$

Where, $w_{fund,i}$ is the weight of stock i in the fund portfolio, and $w_{benchmark,i}$ is stock i's corresponding weight in the benchmark portfolio. According to eq. 2.10 a fund can achieve a high AS when deviating its positions from the benchmark portfolio. For example, a fund with an AS of 0% has identical positions with the benchmark and characterizes an index fund, whereas a fund with an AS of 100% is interpreted as the highest level of active management any fund can achieve. However, it is shown later that it is practically impossible for a fund with a matching benchmark to achieve an AS of 100%[17].
TE is defined by Grinold and Kahn (1999) as the volatility between a funds return and its benchmark return. TE is given by,

$$TrackingError = Stdev[R_{fund} - R_{benchmark}] \tag{2.11}$$

Where, R_{fund} is the fund return, and $R_{benchmark}$ is the fund's benchmark return. Similar to AS, a fund can achieve a high TE by deviating its return relative to the benchmark[21].

[16] In the literature, the momentum factor is also frequently denoted as PR1YR.

[17] This assumes that short-selling is restricted, which may be the case for most retail equity funds[20]. If short positions were allowed AS could exceed 100%.

According to Fama (1972) there are two ways of actively outperform the market or so called types of active mangement: stock selection and/or factor timing[22].
AS captures all active bets relative to the benchmark, i.e. a proxy for stock selection, whereas TE captures factor timing[21][18]. In practice it means that using AS and TE separately does not necessarily make a good measure for evaluating the level of active management.
In fact, it is possible for a fund to obtain a relatively high AS while having a low TE. For example, a fund can have an active investment strategy that consists of holding few overlapping stocks with the benchmark, while being diversified across different sectors. It is also possible for a fund to obtain a relatively high TE while having a low AS. An example hereof could be a fund having an active investment strategy that consists of holding many overlapping stocks with the benchmark, while being less diversified across different sectors.
Hence, a fund may be characterized as active according to one of the two measures, while being characterized as less active by the other measure.
Based on AS and TE measuring different types of active management, Cremers and Petajisto (2009) propose to combine the two measures to form a more accurate approach for determining a fund's level of active management. The result of this approach is graphically illustrated by Cremers and Petajisto (2009) in Figure A.3, Appendix A, by a two dimensional fund classification system.
Based on values of AS and TE, the graph provides an intuitive characterization of four groups of funds with different levels of active management. According to the figure, Closet Index funds (closet indexing) are characterized by having low values of both AS and TE. Factor Betting funds (factor bets) are characterized as having a high TE while a low AS. Stock Picking funds (diversified stock picks) are characterized as having a high AS while a low TE. Concentrated funds (concentrated stock picks) are characterized as having high values of both AS and TE[21]. A fifth group of funds which is not shown in Figure A.3 is Moderately Active funds which are characterized as having medium values of both AS and TE. Concentrated and Stock Picking funds are considered the most actively managed funds, whereas Closet Index and Factor Betting funds are considered the most passive.

[18] Petajisto and Cremers (2009) refer to factor timing as an active strategy, where a fund is betting on systematic factors. An example of betting on systematic factors could be a fund investing solely in one specific sector, which typically is associated with a portfolio of positive correlated stocks. Therefore, factor timing can be interpreted as betting on systematic risk.

CHAPTER 3

Data and Methodology

This chapter outlines a description of the examined data, the applied methodology and statistical tests. The chapter is structured in three main sections: 3.1) Data; Description of the sampled funds and other measures, 3.2) Methodology; Description of the applied methodology, 3.3) Statistical tests; Description of statistical tests for the performance evaluation.

3.1 Data

All mutual fund data used in this thesis was obtained from Morningstar Direct database over the examined time period, namely 28/02/1994 - 31/05/2015, which corresponds to 256 monthly observations. I include existing funds as well as obsolete funds to account for possible survivorship bias. The data is comprised of monthly fund returns (both gross excess returns and net excess returns), monthly benchmark returns, monthly portfolio holdings, monthly total net assets, yearly expense ratios, yearly turnover ratios, monthly average market capitalization, monthly top 10 holdings, monthly number of stock holdings, monthly cash holdings, and historical average manager tenure.

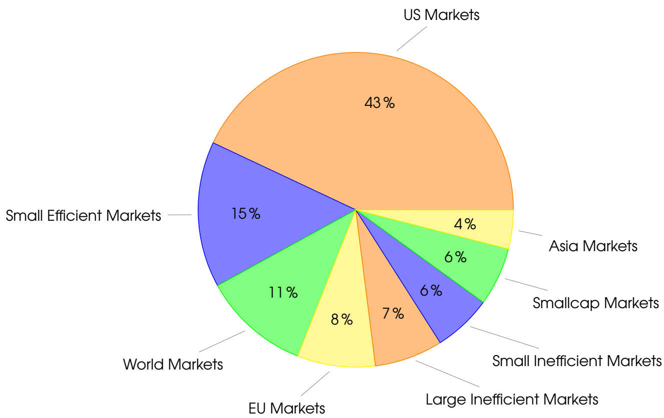
3.1.1 Sample Selection Criteria

For a fund to be included in the dataset, the fund has to meet each component of the criteria that follows:

- The fund is an open-end equity mutual fund.
- The fund is a retail fund.
- The fund is listed as active in the fund prospectus.
- The fund has to have at least $10,000,000 in assets under management.
- The fund has to have portfolio holdings of minimum 6 months, with matching returns.

- The fund's investment area lies within either of the following categories: World Markets, US Markets, Asia Markets, Large European Markets, Large Inefficient Markets, Small Inefficient Markets, Small Efficient Markets, or Smallcap Markets[1].

Figure 3.1: Distribution of sampled funds sorted by eight self-defined investment areas



Source: own contribution

3.1.2 Sample

The initial sample consists of 2,182 actively managed funds whose investment areas vary across different markets. In order to conduct a cross-sectional analysis of the fund performance, I decompose the initial sample of funds into eight subsamples with similar benchmarks, to account for different market characteristics. The subsamples then become broader markets that are structured by first sorting them in regards to geographical investment area, second upon whether the investment area is considered efficient or inefficient[2], third on whether the fund invests in small- or largecap stocks, and fourth by the number of constituents in benchmarks. The distribution of each market is illustrated in Figure 3.1 as a percentage of the total sample. A detailed description of the content of each market can be found in Appendix A, Table A.1. To simplify and strengthen the accurateness of each market, benchmarks with less than

[1]These markets are self-defined and contain group of funds with similar benchmark characteristics. For example, Small Inefficient Markets only include funds, which has either of the following indices as their benchmark: MSCI India, MSCI Russia, MSCI EM Europe, MSCI EM Latin America or MSCI Brazil.

[2]In this thesis, MSCI's classifications of inefficient markets have been used[23].

Table 3.1: Sample coverage of funds with country specific investment areas

Investment area by country	Total Funds: Number of funds	Total Funds: TNA ($ million)	Funds in sample: Number of funds	Funds in sample: TNA ($ million)	Sample coverage: Share of total number of funds	Sample coverage: Share of total TNA
Brazil	632	24,643	5	140	1%	1%
Denmark	30	5,239	28	5,013	93%	96%
Germany*	78	42,116	23	2,924	29%	7%
Hong Kong	12	13,185	5	3,338	42%	25%
India	113	33,531	41	4,915	36%	15%
Italy	42	9,937	33	6,202	79%	62%
Japan*	902	139,445	32	2,680	4%	2%
Korea	783	48,910	5	286	1%	1%
Norway	46	9,751	40	7,719	87%	79%
Russia	27	2,321	25	1,835	93%	79%
Spain	64	8,540	18	1,997	28%	23%
Sweden*	94	49,189	57	33,666	61%	68%
Switzerland*	139	27,767	100	13,620	72%	49%
US*	1,991	3,513,301	639	919,836	32%	26%
Total	4,953	3,927,879	1,051	1,004,179		
Total excl. US	2,962	414,577	412	84,343		

[a] * Indicate both large and smallcap funds.
[b] The table only include those funds in the sample, which have a country specific investment area. Hence, funds investing in regions, e.g. European and Global Markets are excluded.
[c] 'Total Funds' represents the total number of funds within the Morningstar Direct database, per 31/05/2015, screened by the mention criteria.

Source: own contribution with data from Morningstar Direct

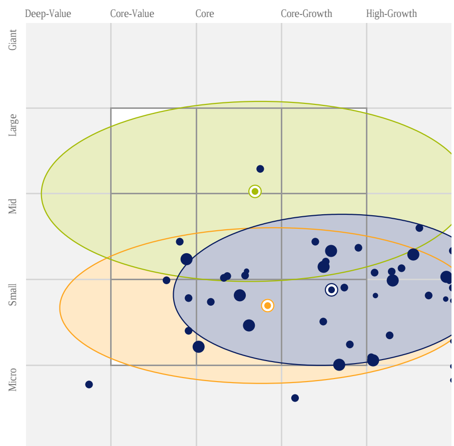
five funds have been removed. Table 3.1 shows the number of funds and the total net assets (TNA) of the sampled funds that have a country specific investment area. From Table 3.1 it is noted that some of the funds in the sample have relatively poor coverage, i.e. funds investing in Brazil, Japan and Korea. However, since the funds are divided into broader markets with similar characteristics, it is not considered to be an issue that some funds in the sample are not fully representative for their market.

3.1.3 Choice of Benchmarks

A prerequisite for accurately examining fund performance is to select the optimal benchmark. Ideally, a benchmark should be aligned with the risk characteristics of a fund's portfolio in order to determine if the fund has delivered abnormal returns or not[24]. Thus, choosing a misplaced benchmark will directly impact the risk-adjusted returns, and yield undesirable findings. In this thesis, selecting the appropriate benchmark is not only important for computing the benchmark-adjusted returns of each fund, but also for the derivation of AS and TE. As a benchmark methodology, for benchmark-adjusted returns, AS and TE, I choose to apply Morningstar Category

assigned benchmarks for all funds rather than each fund's own primary prospectus benchmark[3]. The reason for doing this is that, occasionally, fund managers' self-chosen benchmark does not comply with their actual portfolio holdings, whereas Morningstar Category assigned benchmarks are based on actual portfolio holdings of the fund[25]. This may in part be due to fund managers' tendency to select the benchmark that they intend to outperform. This can potentially lead to conflict of interests[26]. Since the active fund manager's primary objective is to outperform the prospectus benchmark there may be hefty incentives for a fund manager not to choose a perfectly fitted benchmark index - and rather choose one that would make him or her 'look better' performance-wise.
To illustrate how inaccurate a fund's benchmark can be in practice, I plot a style box in Figure 3.2 of the sampled fund, Handelsinvest Nordamerika, along with its selfchosen benchmark, MSCI North America, and the Morningstar Category assigned benchmark, MSCI North America Smallcap[4].

Figure 3.2: Handelsinvest Nordamerika's benchmark vs. its actual holdings



Note: Handelsinvest Nordamerika's actual holdings (as of 31/01/2016) are marked with blue, MSCI North America's holdings are marked with green, and the MSCI North America Smallcap's holdings are marked with orange. The centralized dots within the three circles represent the aggregate investment style of the respective portfolio.

Source: Morningstar Direct

[3]The Morningstar Category assigned benchmark methodology is also known by MPT indices, which typically assigns a broad well-known index as fund benchmark, e.g. a MSCI index. The assigned benchmarks used in this thesis can be found in Appendix A, Table A.1.

[4]The style box is a 3x3 grid, which categorizes each individual stock in a portfolio by its size (market capitalization) and whether the security is considered to be a growth or a value stock, based on multiples such as P/E, P/B, sales growth and cash flow growth, and aggregates it to a portfolio level[27].

The style box shows that while Handelsinvest Nordamerika has committed to outperform large cap stocks, the fund has instead chosen to solely invest in smallcap growth stocks[5]. The style box indicates that the North America Smallcap, which is the Morningstar Category assigned benchmark, captures the fund's actual portfolio holdings better, and thus makes it more suitable for comparison purposes. Using the Morningstar Category assigned benchmarks for deriving AS and TE is also beneficial, since the disparity between a fund and its misplaced benchmark will result in abnormal high values for the two measures[6].

3.1.4 Active Share

AS (eq. 2.10) has been calculated through Morningstar Direct on a rolling monthly basis for each fund, starting from the fund's first portfolio holding date, which in most cases corresponds to the fund's inception date. In order to calculate AS, data on portfolio holdings for each fund and the fund's benchmark is required. I obtain portfolio holdings data from the examined 20-year period from Morningstar Direct. The data coverage on portfolio holdings from 2007 is extensive for most funds, particularly US funds, whereas the data coverage prior 2007 is slim for European and Asia domiciled funds. The vast majority of funds in the sample only file their portfolio holdings once every quarter. This means that for the interim two months, the fund's portfolio holdings and the benchmark holdings are fixed, and won't include any changes that the fund may have made. Nevertheless, AS is not constant in these interim two months because stock prices change, which causes any unequal weights between the positions in the fund and the positions in the benchmark to deviate. I have assigned only one benchmark per fund, which is constant throughout the 20-year period. Calculating AS over such a long time span could potentially result in not being tremendously robust because there is in fact the possibility that the fund could have changed its investment strategy. If this turned out to be the case, the fund would falsely deviate a lot from the new benchmark, causing a high AS. However, I somewhat account for this by removing funds with investment strategies that have undergone restructuring and have experienced a change in benchmark as result. For values of AS, I only include funds in the sample whose values are in the range of 1-99%. The reason for this is that an AS below 1% represents almost entirely an index fund[7], and will thus function as an outlier. An AS above 99% suggests that the fund has a misleading benchmark, since it is close to impossible for a fund to receive an AS close to 100%, even if the fund holds just one stock of the benchmark. Furthermore, most equity open-end mutual funds choose not to engage in short-selling positions, and many are prohibited from short-selling[20]. So, in turn I assume that by restricting short-selling, no AS value can exceed 100%.

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[5]Smallcap stock generally possess a higher risk, a risk the fund fails to mention in their fund prospectus by selecting a misleading benchmark.

[6]An numerical example of a misplaced benchmark can be found in Appendix A, Table A.2.

[7]I include only actively managed funds in the sample, however some funds may mistakenly have been tagged as index funds in the database.

3.1.5 Tracking Error

I calculate the annualized ex-post tracking error (eq. 2.11), through Morningstar Direct, for each month based on daily gross fund returns. I use a rolling window of 180 days, starting 31/08/1993, to get the standard deviation of the funds' excess returns at the end of each month.

3.1.6 Risk Measures

To determine if the group of funds with different levels of active management possesses higher risk, I apply two risk measures: VaR (Value at Risk, eq. 3.1), and ES (Expected Shortfall, eq. 3.2). Rather than computing the risk measures on an asset-based level, VaR and ES have been derived from aggregated mean return series for each examined fund group. I assume the return series to be normally distributed with a mean and standard deviation equal to the fund group return series. The computation of VaR and ES is based on monthly returns for the period 28/02/1994 - 31/05/2015 with a 95% confidence level. Given the normal distribution assumption, the two risk measures are given by,

$$VaR_{(0.05,normal)} = \mu_{group} - 1.65\sigma_{group} \tag{3.1}$$

Where, μ_{group}, σ_{group} is the mean, and standard deviation of the group returns[11].

$$ES = \frac{1}{0.05} exp(\mu_{group}) N[-\sigma - F(0.95)] - 1 \tag{3.2}$$

Where, N is the cumulative standard normal, and F is the inverse of the cumulative standard normal[28][11][8].

3.2 Methodology

In order to examine the performance of the five different groups of active management I take an approach inspired by Petajisto (2013)[9] and thus divide all funds into 25 different portfolios based on the calculated AS and TE values. The 25 portfolios represent the five different groups, namely: Closet Index funds, Factor Betting funds, Moderately Active funds, Concentrated funds and Stock Picking funds[10]. The portfolios are constructed from relative AS and TE quintiles for each monthly observation to account for different market characteristics, such as the size of the benchmark. Hence, the 25 portfolios are made of 25 different outcomes of AS and TE quintiles. For example, one portfolio consists of funds with both AS and TE values within the 80-100% range, whereas a second portfolio consists of funds with AS quintiles within

[8] The derivations of VaR and ES have been carried out in R, which can be found in Appendix E.
[9] And Cremers and Petajisto (2009).
[10] Table A.3 in Appendix A illustrates how the portfolios are divided into the five groups.

60-80% range, etc. By constructing portfolios on a monthly basis, I allow funds to switch groups over time, which is preferable since funds occasionally change its AS and TE values. An illustration hereof can be found in Appendix A, Figure A.2, which also shows the sample density over time. For instance, the fund Enter Sweden, in 01/03/2015, was marked as a moderately active fund based on an AS of 56.11% and a TE of 4.91%. A month later, the fund was marked as a stock picking fund, since its AS and TE had increased to 57.38%, and 5.01%. The switch in categorization can be attributed to an increase in both AS and TE, but may have also been caused by reduced relative quintiles for the market. The disadvantage of using relative quintiles is that, in theory, a fund with a constant AS and TE over time can be considered more active if the fund's peers have on average become more passive, and have thus pulled down the quintiles of AS and TE[11].

After constructing the portfolios, I allocate the funds with an equal weight into the five different active groups, for each monthly observation, based on Table A.3 in Appendix A. I then match each group of funds to their related benchmark-adjusted returns, and take the arithmetic average of each monthly observation across all funds in the period 28/02/1994 - 31/05/2015. This leaves me with five benchmark-adjusted return series for the five groups of active management. These five groups are then further sorted into the eight markets. To empirically measure any statistical significant performance, and adjust for risk factors across the eight markets, I apply regression models of the two traditional risk-adjusted performance measures: Jensen's alpha, eq. 2.1 and Carhart's four-factor model, eq. 2.2. I thus seek to test the if the performance on each market is statistically different from zero, i.e. the null hypothesis, $H_0 : \alpha = 0$, using both models. Aside from using the two traditional risk-adjusted performance measures, I tend to explain the variation in fund returns by alternative regression models, assisted by a comprehensive correlation analysis, with self-selected fund-specific variables.

3.2.1 Applied Variables in Regression Models and Correlation Analysis

This subsection list the applied variables in the performance models (applied in Chapter 7), as well as the applied variables for the alternative regression models and the correlation analysis (applied in Chapter 8).

3.2.1.1 Variables of Jensen's index and Carhart's four-factor model

For the two performance measures, Jensen's alpha and Carhart's four-factor model, I use monthly benchmark-adjusted returns as the dependent variable i.e.,

$$R_{benchmark-adjusted,i} = R_{fund,i} - R_{benchmark,i} \tag{3.3}$$

[11]It would have the opposite effect, if the peer funds would have become more active.

Where, $R_{fund,i}$ is the return of fund i, and $R_{benchmark,i}$ is the return of fund i's benchmark[5]. In the two performance models, I test the benchmark-adjusted returns both before and after fees. The benchmark-adjusted gross and net returns are equivalent to gross and net excess returns over each fund's assigned benchmark. Benchmark-adjusted gross and net returns are expressed in percentages. Additionally, they are calculated by taking the change in the monthly Net Asset Value (NAV), including any reinvested capital gain distributions from the month, and the dividing this by the starting NAV[11], i.e.,

$$FundReturn(\%) = \frac{NAV_1 - NAV_0 + CapitalGainDistribution}{NAV_0} \tag{3.4}$$

The difference between gross and net returns is that, the net returns have been adjusted for on-going expenses, such as management, administrative and 12b-1[12] fees, whereas gross return is simply the raw return. For net returns, sales charges, such as front-end loads, deferred loads and redemption fees, are not factored in, as they have tendency to vary from investor to investor[29][30]. Each return series is expressed by the geometric mean. The data quality of reported returns is considered adequate for the examined time period.

As factors for Jensen's alpha and Carhart's four-factor model, I use country specific factors for each market, provided by Kenneth R. French[31], to capture the best fitted risk-adjusted returns as possible. I use the following monthly risk factors: MKT, HML, SMB and MOM (described earlier). Table A.4 in Appendix A shows each market and its assigned country specific factor. Since the markets contain funds with different geographical investment areas, the factors are not considered to be fully representative of each market. Nevertheless, using country specific factors for each market is assumed to a better proxy than the use of one global factor across the entirely of the sample.

3.2.1.2 Alternative Regression Models and Correlation Analysis

Similar to the two performance models, I apply benchmark-adjusted gross and net returns as the dependent variable. The purpose of the alternative regression models and the correlation analysis is solely to investigate variables that are causing the variation in fund returns. Therefore, the alternative regression models and the correlation analysis should not be seen as a replacement for the two performance measures, Jensen's alpha and Carhart's four-factor model. For this purpose I have selected eight independent fund-specific variables, which have been screened in the Morningstar Direct database. The following variables have been selected based on a possible relationship to fund returns.

[12]Only relevant for US domiciled funds.

The first fund-specific variable selected is the monthly fund size, which is the TNA managed by the fund. To make fund size interpretable, the natural logarithm of each fund's TNA is taken. The second chosen variable is the annually reported expense ratio, which only factors in the yearly expenses of running a fund. The expense ratio for each fund has been converted into monthly figures. Third is the portfolio turnover ratio, which measures the trading activity of a fund[32]. Similar to the expense ratio, portfolio turnover is only reported annually and therefore has been converted into monthly figures as well. The fourth is the total net number of stock holdings in a fund's portfolio. Occasionally, funds hold a large number of stocks, e.g. over 1000 stocks. I consider those funds to be outliers. To prevent the variable from being biased upwards, funds whose stock holdings exceed 1000 have been excluded. The fifth variable is the top 10 holdings, expressed as a percentage weight for the 10 largest stock holdings in a fund's portfolio. Sixth is the currently held cash position, which is expressed as a percentage of a fund's total assets. Seventh is the average market capitalization (AMC), which measures the mean size of all the stock holdings held by the fund[13]. Lastly, the manager tenure, which is the longest historical tenure a manager has been with a fund, is the eight and final independent variable chosen. Manager tenure is given as a single observation. Thus, in order to get a time series, the average manager tenure for each fund is held constant over the period for which the manager has managed the fund.
Table 3.2 shows the descriptive statistics for the selfchosen explanatory variables for all funds. The upper part of the table depicts the time series average for the entire examined period, whereas the lower part of the table illustrates a snapshot of four separate years, i.e. 1994, 2001, 2008, and 2015. It is clearly apparent that the data coverage is rather poor in 1994, but then significantly improves beyond 2008 and until 2015.
Poor data quality of the fund-specific variables, in the 90's, causes a general concern when taking the time series average because funds with missing data will automatically be left out of the monthly observation, and treated as obsolete funds. This is problematic since the remaining funds will be assigned a higher weight, which consequently creates a sample of funds that is too small to represent the actual sample size. For example, in 1994, there were 223 living funds in the sample, but only 29 funds had reported the number of stocks held. A sample of 29 funds is unlikely to be fully representative for that variable out of the actual 223 funds. Hence, the data quality may in some instances cause the fund-specific variables to be biased up- or downwards to a certain degree. However, the issues with data quality, are only considered widespread for the selected fund-specific variables prior 2001 as they are not consistently reported for each fund.

[13] AMC is given by,

$$AMC = \frac{\sum_{i=1}^{n} w_i ln(MC_i)}{\sum_{i=1}^{n} w_i} \tag{3.5}$$

Where, w_i is the portfolio weight of stock i, MC_i is the market cap of stock i, and n is the total number of stocks held by the fund (AMC methodology is provided by Morningstar Direct).

Table 3.2: Descriptive statistics of explanatory variables

Time Series Average (all funds): 1994-2015

Statistic	Fund Size	Exp. Ratio	Turnover	No. Stocks	Top 10 Holdings	Cash	Avg. Market Cap	Manager Tenure
#Obs	225	256	256	256	256	204	254	233
Mean	19.011	0.001	0.071	99.191	0.357	0.051	9.286	14.408
St. Dev.	0.219	0.0001	0.012	15.252	0.033	0.023	0.450	5.015
Median	19.025	0.001	0.069	95.906	0.366	0.043	9.409	14.102

Yearly Average (all funds): 1994; 2001; 2008; 2015

Statistic	Fund Size	Exp. Ratio	Turnover	No. Stocks	Top 10 Holdings	Cash	Avg. Market Cap	Manager Tenure
#Obs	273;597; 1,545;2,203	259;465; 1,490;1,710	231;491; 1,488;948	29;279; 1,265;2,059	36;274; 1,260;2,052	NA;11; 219;1,872	NA;273; 1,257;2,054	NA;130; 611;1,947
Mean	18.83;19.3; 19.43;19.23	0.001;0.001; 0.001;0.001	0.067;0.089; 0.082;0.054	141.6;122.6; 142.6;168.48	0.31;0,35; 0.38;0.36	NA;0.03; 0.04;0.02	NA;9.54; 9.74;9.85	NA;18.43; 12.15;6.84
St. Dev.	2.35;2.42; 1.83;1.73	0.000;0.001; 0.001;0.001	0.000;0.16; 0.08;0.05	29;479; 1,461;2,424	0.12;0.14; 0.2;0.4	NA;0.03; 0.09;0.05	NA;1.26; 1.06;1.03	NA;3.27; 3.94;4.5
Median	18.99;19.31; 19.45;19.14	0.001;0.001; 0.001;0.001	0.06;0.06; 0.05;0.04	74;75; 67;61	0.29;0.31; 0.33;0.33	NA;0.00; 0.02;0.01	NA;9.77; 9.99;9.99	NA;17.28; 10.83;5.83

[a] Each yearly statistic is separated by ;
[b] Number of living funds in the sample were in year 1994: 223 funds; year 2001: 1,047 funds; year 2008: 1,773; and year 2015: 2,182 funds.

Source: own contribution (data from Morningstar Direct)

3.3 Statistical Tests

To measure the performance of each group of funds, I perform a total of 176 time series regression models using both Jensen's alpha and Carhart's four-factor model. Out of the 176 models, only 15 performance models were useful in explaining a fraction of the variation in returns, according to R^2 and the adjusted R^2. In this section, I examine regression diagnostics for these 15 models, where I specifically test for linearity, homoscedasticity, normality, multicollinearity and autocorrelation[33][34]. The test results of the model diagnostics for the 15 models are illustrated in Table 3.3 alongside with the models' R^2, the adjusted R^2, and the standard error estimates. Table 3.3 show 11 of the 15 models are fulfilling all the model diagnostics (marked with green), and four of the models are not (marked with red). In the following I will briefly elaborate on how the model diagnostics are performed, whereas a more detailed analysis of the model diagnostics can be found in Appendix D.

Firstly, I test if there is a relationship between the dependent and the independent variables (linearity) by plotting the residuals against the predicted returns in a scatter plot[14]. In order for the linearity assumption to be fulfilled, there should be no pattern in the scatter plots[33]. While all of the 15 performance models show some degree of a pattern, 2 models have been identified as having a clear pattern. These two models are 'World Markets - Factor Betters Net Carhart' and 'US Markets - Factor Betters Net Carhart'.

Secondly, I test for homoscedasticity, i.e. the existence of constant variance among

[14]The linearity plots for the 15 models can be found in Appendix D.

Table 3.3: Model diagnostics for most significant models

Model				Model Diagnostics							
Market	Group	Gross/ Net	Jensen/ Carhart*	Linearity (Appendix D)	Normality (Appendix D)	Homosce-dasticity (Appendix D)	Multicoll-inearity (Appendix D)	Auto-correlation (Appendix D)	R Square	Adj. R Square	Std. Error Estimate
All Sampled Funds	Closet Indexers	Gross	Carhart	Pass	Pass	Pass	Pass	Pass	0.028	0.013	0.004
All Sampled Funds	Stock Pickers	Gross	Carhart	Pass	Pass	Pass	Pass	Pass	0.041	0.023	0.015
Large Ineff. Markets	Closet Indexers	Net	Carhart	Pass	Pass	Pass	Pass	Pass	0.0513	0.025	0.004
US Markets	Closet Indexers	Net	Carhart	Pass	Pass	Pass	Pass	Pass	0.042	0.027	0.004
Smallcap Markets	Factor Betters	Gross	Jensen	Pass	Pass	Pass	Pass	Fail	0.042	0.029	0.023
World Markets	Factor Betters	Net	Jensen	Pass	Pass	Pass	Pass	Fail	0.033	0.025	0.014
World Markets	Factor Betters	Net	Carhart	Fail	Pass	Pass	Pass	Fail	0.051	0.016	0.014
US Markets	Factor Betters	Net	Carhart	Fail	Pass	Pass	Pass	Pass	0.082	0.061	0.014
Small Ineff. Markets	Moderately Active	Gross	Jensen	Pass	Pass	Pass	Pass	Pass	0.031	0.025	0.013
Small Ineff. Markets	Moderately Active	Gross	Carhart	Pass	Pass	Pass	Pass	Pass	0.051	0.025	0.013
Large Ineff. Markets	Moderately Active	Net	Carhart	Pass	Pass	Pass	Pass	Pass	0.045	0.018	0.007
World Markets	Concentrated	Gross	Jensen	Pass	Pass	Pass	Pass	Pass	0.019	0.012	0.027
World Markets	Concentrated	Gross	Carhart	Pass	Pass	Pass	Pass	Pass	0.045	0.016	0.027
Smallcap Markets	Stock Pickers	Gross	Jensen	Pass	Pass	Pass	Pass	Pass	0.026	0.019	0.014
Smallcap Markets	Stock Pickers	Gross	Carhart	Pass	Pass	Pass	Pass	Pass	0.03	0.01	0.014

[a] Approved models are market with green, and disproved models are marked with red.
[b] Pass/fail indicates an approved/disproved model diagnostic.
[c] * distinguishes between the two performance measures, Jensen's alpha and Carhart's four-factor model.

Source: own contribution

the residuals. This is done by eyeballing the residual plots, used for linearity tests, to see if the residuals are unequal (heteroscedasticity) (ibid.). For the 15 performance models, the variance is fairly constant, thus no heteroscedasticity is detected[15].
Thirdly, I test for whether all variables are normally distributed by a quantile-quantile plot (normality). In order for this assumption to be met, the points has to fall roughly on a 45 degree line (ibid.). For all 15 performance models this assumption is met[16].
Fourthly, I test for multicollinearity, i.e. the independence of each included explanatory variable. In order to detect multicollinearity I have used the Variance Inflation Factor (VIF) statistic, where a value above 10 suggests strong multicollinearity[35]. I find that none of the 15 performance models violates this assumption[17].
Finally, I test for serial independence among the residuals (positive or negative first-order autocorrelation), using the Durbin-Watson statistic with a lag of 1[33][36]. I find that three out of the 15 performance models violate the autocorrelation assumption[18].

[15] From the linearity plots in Appendix D.
[16] Normality plots for the 15 models can be found in Appendix D.
[17] VIF values for the 15 models can be found in Appendix D.
[18] Durbin-Watson statitics for the 15 models can be found in Appendix D.

CHAPTER 4

Implications of Applying Active Share in Different Markets

In this chapter, the purpose is to address sub-question *a*:

- What are the implications for applying the active share measure for funds and benchmarks with different characteristics?

According to Petajisto's (2013) AS methodology, a fund is considered active if it has an AS above 60% and categorized as a Closet Index fund if the AS is below 60%[37]. One of the criticized areas of the AS methodology is that using the threshold (or cut-off point) of 60% can be somewhat biased as it does not take two influential variables into consideration, namely 1) the fund's benchmark size measured by the number of constituents, and 2) the number of stocks held by the fund. Consequently, it is difficult and sometimes impossible for funds in some markets to achieve sufficiently high AS and be categorized as active. The reason is often that a fund's investment area does not contain enough investable stocks to deviate sufficiently from the benchmark. For instance, the US equity market generally has broader benchmarks containing many constituents such as the S&P 500 and the Russell 1000 as opposed to the European equity market, which normally has narrower benchmarks, e.g. the OMX C20 and OMX Stockholm 30 that have only 20 and 30 stocks in their indices, respectively. In other words, funds with broader benchmarks have a wider range of stocks for funds to choose from and therefore also a better opportunity to achieve a high AS.

The chapter is setup into seven sections: 4.1) Approach; Description of the model applied, the Monte Carlo Model, to define the implications for applying the AS measure for funds and benchmarks with different characteristics. 4.2) Model assumptions; An outline of applied assumptions to ensure relevance and usefulness of model output. 4.3) Model findings; Description of the model key findings. 4.4) Discussion of assumptions; Discussion of the applied assumptions and relevance in practice. 4.5) Test of robustness of the Monte Carlo model; Test of the model's applicability on two sampled funds using randomized benchmark weights. 4.6) Test of robustness of alternative Monte Carlo Model; Tests of an alternative model's applicability on two sampled funds using randomized fund portfolio weights. 4.7) Conclusion; Sum up of the findings in terms of implications for applying the AS measure for funds and benchmarks with different characteristics of the Monte Carlo Model.

4.1 Approach

In the following I define specific thresholds for funds to categorize whether they are truly active or in fact Closet Index funds. I will do this through a Monte Carlo simulation (MC), where I construct a model that can specify a cut-off point based on 1) the fund's benchmark size measured by the number of constituents, and 2) the number of stocks held by the fund. By holding the fund's portfolio weight of stocks equally constant while randomizing the weights in the benchmark, I simulate a sequence of different outcomes by changing the benchmark sizes (denoted n) and fund portfolio sizes (denoted q). The outcomes are, n=20, n=30, ..., n=1000 for benchmark sizes, and q=10, q=11, ..., q=40 for fund portfolio sizes. Each outcome has separately been simulated 10,000 times. When simulating each outcome separately, I take the maximum, the minimum, and the mean values of AS to determine the range in which AS values can fall within. This enables me to generalize the cut-off point from the AS range for each simulated outcome.

4.2 Model Assumptions

In order to run the model with the highest chance of a useful output, I have defined and applied a set of assumptions. The assumptions are briefly mentioned below and further discussed in section 4.4.

1. Each active fund's primary intention is to maximize its returns by only selecting stocks that the fund manager based on fundamental analysis find undervalued. Hence, fund managers do not focus on AS while constructing the portfolio.

2. Each weight of a benchmark constituent is randomly and independently deviating from one another, and this varies across different benchmarks.

3. Each active fund attempts to diversify the different weights of stocks equally within its portfolio to minimize the exposure of idiosyncratic risk.

4. Short selling is not allowed. Thus, the sum of the fund's portfolio and the corresponding benchmark has to equal 100%. Restricting short selling means that AS can not exceed 100%.

5. A fund is not able to invest in stocks outside of its benchmark.

The objective function for the model is,

$$ActiveShare = \frac{1}{2}\sum_{i=1}^{N} |w_{fund,i} - w_{benchmark,i}| \tag{4.1}$$

Where,
$w_{fund,i}$ is the weight of each stock i in the fund portfolio, and can range from q=10 to q=40 in number of stocks. Each stock in the fund portfolio is weighted equally, $w_{fund,i} = \frac{1}{q}$, and held constant. $w_{benchmark,i}$ is the weight of each constituent i in the benchmark portfolio and can range from n=20 to n=1000 in number of constituents[1]. For each weight in benchmark I generate a continuous random variable, denoted X, which is uniformly distributed between [0,1].

$$X \sim U([0,1]) \tag{4.2}$$

To obtain a total weight of 100% of all constituents in the benchmark portfolio, I divide a sequence of IID random variables, $X_1, X_2, ..., X_n$, by the sum of the total random variables to ultimately arrive at a random weight for each constituent in the benchmark,

$$w_{benchmark,i} = \frac{X_i}{\sum_{i=1}^{n} X_i} \tag{4.3}$$

And to prevent negative values,

$$|w_{fund,i} - w_{benchmark,i}| \tag{4.4}$$

In order to get a good estimation of AS, the simulation is repeated 10,000 times, where the weight of each constituent in all of the benchmarks is set to change randomly every time.

4.3 Model Findings

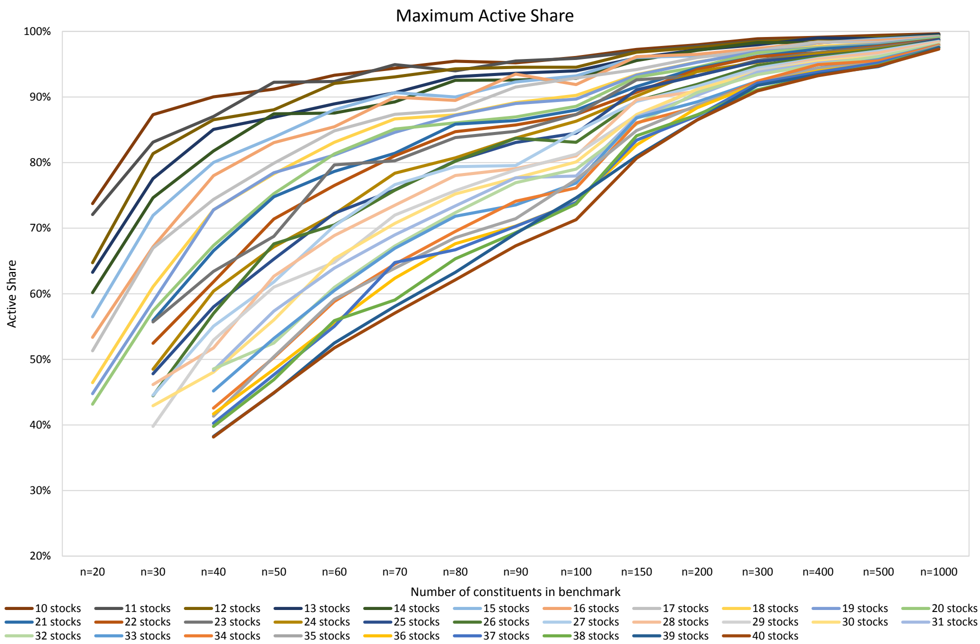
The model ultimately illustrates a few key findings. First, the model show that funds with a larger benchmark have higher AS values. More specifically, when the number of constituents in the benchmark increases, n $\rightarrow \infty$, the random weights in the benchmark get arbitrarily close to 0% (however, each weight will always be greater than 0%) and AS will thus converge towards 100%. As short selling is assumed restricted, the AS will never reach 100%[2]. Figure 4.1 illustrates AS as a function of number of constituents in the benchmark. The graph shows maximum simulated

[1] The sample's smallest benchmark, MSCI Denmark NR DKK, consists of 20 constituents, whereas the largest benchmark, Russel 3000 TR USD, has 3000 constituents. The model's largest benchmark consists of 1000 constituents, which is considered sufficient for illustration purposes.

[2] The reason is that, in theory, a fund has to hold at least one stock that overlap with the benchmark. Hence, no matter how big n becomes AS will always be less than 100%.

AS values[3] (vertical axis) for 30 different funds that vary in number of stocks held, ranging from q=10, q=11, ..., q=40, and the number of constituents spanning from n=20, n=30, ..., n=1000 (horizontal axis).

Figure 4.1: Maximum simulated active share values of 30 funds with different number of stocks

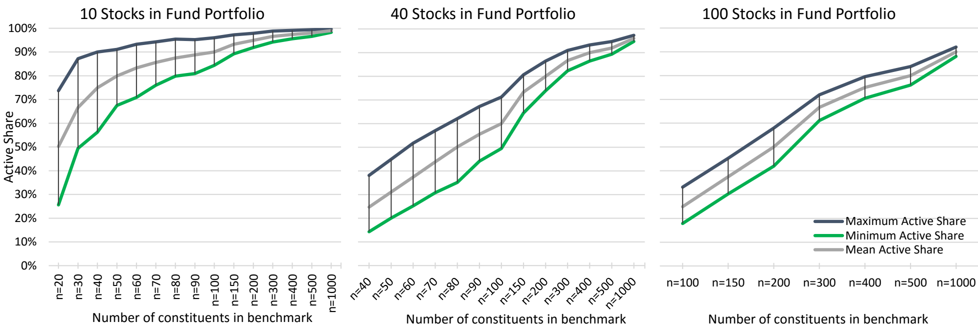


Source: own contribution

Secondly, the model shows that it becomes harder to achieve a high AS for funds that are holding a large number of stocks in their portfolio, i.e. q is high, compared to those holding fewer stocks. This is shown in Figure 4.2, which illustrates the maximum, minimum and mean AS of three separate funds with holdings of 10, 40 and 100 number of stocks, respectively. The graph shows that AS increases faster for a fund with 10 stocks when the number of constituents in the benchmark increases than for a fund with 40 and 100 stocks. Thus, holding fewer stocks makes it easier for a fund to obtain a higher AS as illustrated in Figure 4.1. On a site note this mean that, all other things held constant, funds with less diversified portfolios are able to achieve higher AS values, compared to funds with more diversified portfolios.

[3] Similar graphs for minimum, and mean AS can be found in Appendix B, Figure B.1 and B.2.

Figure 4.2: Maximum, minimum and mean active share of three funds holding 10, 40 and 100 stocks, respectively



Source: own contribution

Table 4.1: Table of maximum, minimum and mean active share for the funds holding 10, 40 and 100 stocks

Number of constituents in Benchmark		n=20	n=30	n=40	n=50	n=60	n=70	n=80	n=90	n=100	n=150	n=200	n=300	n=400	n=500	n=1000
10 stocks	Max AS	73.7%	87.2%	90.0%	91.1%	93.3%	94.3%	95.4%	95.2%	96.0%	97.2%	97.9%	98.8%	99.1%	99.4%	99.6%
in fund	Min AS	25.6%	49.4%	56.2%	67.5%	70.9%	76.0%	79.8%	80.9%	84.4%	89.2%	91.9%	94.2%	95.6%	96.6%	98.3%
portfolio	Mean AS	50.2%	66.6%	74.9%	79.9%	83.3%	85.6%	87.5%	88.8%	90.0%	93.3%	94.9%	96.6%	97.4%	98.0%	99.0%
40 stocks	Max AS	N/A	N/A	38.1%	44.9%	51.7%	57.0%	62.1%	67.2%	71.2%	80.6%	86.4%	90.9%	93.2%	94.7%	97.3%
in fund	Min AS	N/A	N/A	14.3%	20.1%	25.2%	30.8%	35.1%	44.1%	49.5%	64.5%	73.9%	82.3%	86.4%	89.3%	94.7%
portfolio	Mean AS	N/A	N/A	24.7%	31.1%	37.4%	43.8%	50.1%	55.5%	60.0%	73.3%	80.0%	86.6%	90.0%	91.9%	96.0%
100 stocks	Max AS	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	33.1%	45.3%	57.9%	71.9%	79.5%	83.8%	92.0%
in fund	Min AS	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	17.8%	30.3%	42.0%	61.1%	70.5%	76.0%	88.1%
portfolio	Mean AS	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	24.9%	37.5%	50.1%	66.7%	75.0%	80.0%	90.0%

Note: N/A represents a fund that are holding stocks outside its benchmark, thus according to Assumption 5 these AS values are not computed.

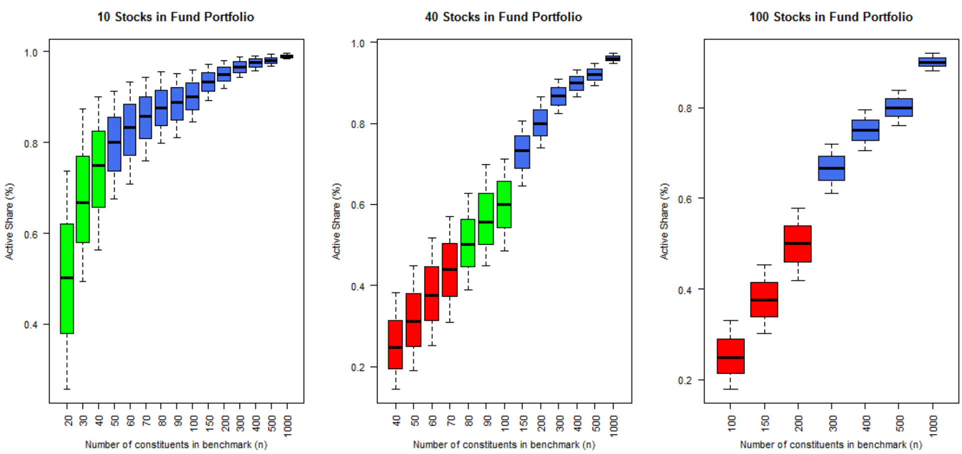
Source: own contribution

The third finding is based on the above two findings and suggests that it is possible to define specific thresholds for specific funds to categorize whether they are truly active or in fact Closet Index funds.
Table 4.1 lists the simulated AS boundaries of Figure 4.2, i.e. the maximum, minimum and mean AS values[4]. A complete overview of all the simulated outcomes with different benchmark and fund size can be found in Appendix B, Table B.1 and B.2. The rationale behind the boundaries of AS can be used as a sanity check for funds that have been identified either as truly active or Closet Index funds, by the original 60% cut-off point set by Petajisto (2013). If the actual fund holdings reach an AS higher than the average between the lower and higher boundaries, the fund is to be considered truly active.

[4]I should be noted that the AS mean listed in Table 4.1 is the simulated mean, and not the plain mean between maximum and minimum.

For example, if a fund with q=40 stocks and a benchmark with n=70 constituents has an AS of 49%, the fund would be categorized as a Closet Index funds following Petajisto's (2013) cut-off point (49%<60%). According to the model assuming portfolio weights must be equally weighted, the fund's maximum achievable AS is 57%. Consequently, the fund cannot be categorized as truly active using the 60% cut-off point[5]. Ideally, the cut-off point should be based on how many stocks the fund holds and the number of constituents in the benchmark. A way to accomplish this could be to use Petajisto's argument, which imply that a fund has to place 10% on top of the mean in active bets in order for the fund to be truly active (corresponding to the original AS cut-off point of 60%). Adding 10% to the AS mean yields a new modified cut-off point, $0.438 * 1.1 = 0.4818$. The new modified cut-off point of 48.18% is lower than the fund's AS of 49%, which marks the fund as truly active as opposed to original cut-off point, where the fund was classified as a Closet Index fund.

Figure 4.3: Boxplot of the three funds with holdings of 10, 40 and 100 stocks



Note: The red boxplots represent those funds, which can only get an AS below the original 60% cut-off point. The green boxplots represents those funds, which can get an AS above, or below the 60% cut-off point, and the blue boxplots represents those funds which can only get an AS above the 60% cut-off point.

Source: own contribution

The case above is illustrated in a boxplot, Figure 4.3, for the three previous funds with q=10, q=40 and q=100 stocks. The boxplots show that it is unfair to use the 60% cut-off point for all funds as some due to smaller benchmark have capped

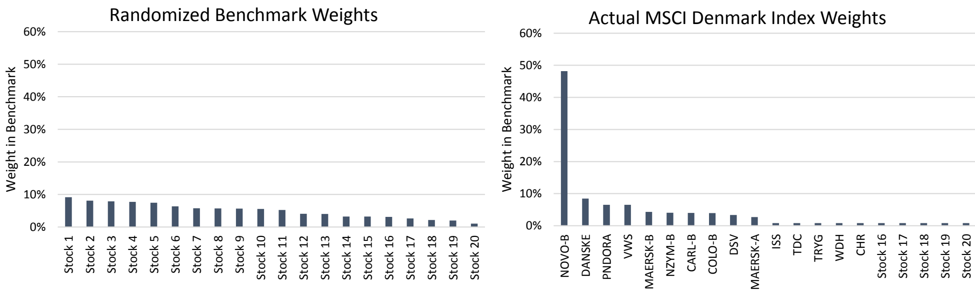
[5]If criterion requiring equal weights in the portfolio was repealed and the weights were reallocated or the number of stocks reduced, it would be possible to get an AS above 60%.

maximum AS values below Petajisto's threshold. Based on the model's maximum and minimum AS boundaries, it can be argued that referring to absolute AS values is not an appropriate way to determine the cut-off point between truly active funds and Closet Index funds. The reason is that it is harder for funds with a small benchmark to achieve a high AS and equally hard for funds with a large benchmark to achieve a low AS. Instead of absolute AS values, it is appropriate to use relative AS values when attempting to get a more relevant proxy for a cut-off point taking the number of constituents in benchmarks into account.
However, in reality and in practice, the majority of the sampled funds have stocks outside of their benchmarks and are thus beyond the simulated range. The reason for this is that stocks invested outside of the benchmark are treated as active positions and thus increases the AS value for the funds.

4.4 Discussion of Assumptions

This section discusses whether the applied model assumptions are relevant in practice. Assumption 1: Active managers only select stocks based on their approach to fundamental analysis. This assumption is critical. If not included, an active portfolio manager could maximize AS of the fund by refraining from buying the top weighted constituent in the benchmark for the portfolio. For example, the MSCI Denmark NR DKK's top 1 constituent, Novo Nordisk A/S, accounts for approximately 47% of the index[38]. In other words, If a portfolio manager's intention was to increase AS for the fund, she could choose to do so by deliberately not buying the stock, but instead further increase the AS through larger weights on stocks with lower weights in the benchmark.
Assumption 2: Benchmark portfolio weights deviate randomly across benchmarks as well as independently. The intention behind this assumption is to justify the allocation of random weights for the benchmark constituents when constructing a general proxy for all benchmarks in the model. In practice, the constituents' weights in a benchmark tend to vary substantially from one another. Figure 4.4 plots two histograms, which show the MSCI Denmark Index and a randomized set of benchmark weights made from a uniform distribution.
When looking at the MSCI Denmark Index, a highly positive skewed distribution is clearly apparent and driven by one large constituent, Novo Nordisk A/S (Novo-B). Having many large single weightings across benchmarks is problematic for the model as the random weights will not approach such extreme values even over the course of 10,000 simulations, and therefore undermine the real index weight. The MSCI Denmark benchmark is naturally its own, but it is likely that there may be other markets with large corporations dominating the index in a similar manner. This is presumably more widespread in smaller benchmarks as the size makes it easier for larger corporations to dominate it compared to in larger benchmarks. In other words, the assumption of randomizing the weights does not cope well with these types of indices.

Figure 4.4: Weight distribution of randomized benchmark weights and the actual weight of the MSCI Denmark NR DKK



Source: own contribution (MSCI Denmark Holdings from Morningstar Direct)

As an alternative to randomizing the benchmark weights, one could randomize the fund portfolio weights. However, the constituent weights in the benchmark are likely to deviate significantly more than the weights in the fund's holding. For instance, it would be unlikely to see a fund manager initiate a new position with a weight of less than 0.01% or more than 15%, whereas it is more likely to see a benchmark with constituent weightings that can deviate more substantially[6]. Furthermore, it would not be optimal to construct a benchmark of fixed weights as benchmark indices tend to have different composite weight methodologies. For example, the Dow Jones Industrial Average index (DIJA) bases each constituent weight on the relative size of its share price[39], while the S&P 500 EWI (SPW) bases the weight of each constituent equally and rebalances every constituent each quarter[40]. The NASDAQ Composite Index (COMP) employs a market capitalization-weighted index[41]. The different weighting methodologies suggest that the best proxy for a general benchmark is constructed using random weights. While there may be a few exceptions, like the MSCI Denmark index, on average, the use of random weights seems optimal. In other words, randomizing the benchmark weights remain a preferred assumption despite coping less well with small benchmarks.
Assumption 3: Active managers seek to diversify their portfolio weights equally to lower the idiosyncratic risk. As most, if not all, fund managers seek to diversify their portfolio to limit unnecessary risks, the assumption is considered reasonable. Also, it is typical that financial advisories have diversification required legally for the purpose of investor protection. In the MC model, completely equal weights are applied, $w_{fund,i} = \frac{1}{q}$. In practice, this is difficult, if not impossible, as portfolio weights would have to be adjusted dynamically to constantly ensure equal weights.

[6]E.g. the lowest constituent weight in the S&P 500 Index is 0.0001%, whereas the largest constituent weight in MSCI Switzerland Index is 21.34% (31/05/2015). Source: Morningstar Direct.

Technically, this may cause some estimation errors meaning that the cutoff point will not be completely accurate.
Despite assuming that active managers seek to diversify, too much diversification can also work as a constraint for maximizing AS. If too high diversification, i.e. a large number of stocks, it will prevent active fund managers from deviating its stock weights relative to the benchmark weights. This goes in line with Assumption 1 that the managers' primary intention for the stock selection process is not related to maximizing AS. In addition to diversification, regulation is another constraint for AS. E.g. in Denmark, some equity funds are restricted from placing more than 10% of their capital in a single stock within their benchmark[42][43]. This inhibits active fund managers from deviating substantially from the benchmark weights and thus limits how high AS can become.
Assumption 4: Short selling is not allowed. This assumption is included and applied to simplify the analysis. Furthermore, it is believed to be reasonable as some open-end equity mutual funds are not allowed to take short positions[20].
Assumption 5: No funds are allowed to invest in stocks outside of their benchmark. This is a key assumption to ensure that funds do not invest in stocks that are outside of the fund's assigned benchmark and thus impact- and skew AS upwards.

4.5 Test of Robustness of the Monte Carlo Model

The purpose of this section is to test the model's applicability on two sampled funds using randomized benchmark weights. In order to determine whether the MC model can be applied to adjust cut-off points for various funds and benchmarks sizes, the true AS of two sampled funds are being tested to see if they fall within their simulated AS ranges. In the thesis, true AS is defined as a fund portfolio of stocks with total overlap to the benchmark, i.e. the funds cannot hold any stocks outside of the benchmark. The two selected funds from the sample are; TCW Concentrated Value N and Lannebo Sverige, which have S&P 500 TR USD and MSCI Sweden NR SEK as their benchmarks, respectively. Each fund has different portfolio sizes (q=28, q=13) and benchmark sizes (n=500, n=30).

In terms of approach, first step is to look at the actual portfolio holdings of the two funds and ensure that all assumptions are met. This showed that both of the funds were actually holding stocks outside of their benchmark and thus conflicting with Assumption 5. In order to comply with the assumptions and improve the relevance of the output, the identified stocks are removed from the portfolios and remaining stocks are reallocated to restore previous weights amongst them. The actual test is to run the simulation for both funds' AS, again with randomization of each weight in the benchmark, while adjusting for the fund's portfolio weights.
The results are shown in Table 4.2 and illustrated for a number of different outcomes in Figure 4.5. The table and figure both show that Lannebo Sverige falls within

the range of the simulated AS values and well above the mean AS, whereas TCW Concentrated Value N's true AS is lower than the simulated minimum AS. In other words, Lannebo Sverige would be considered active, whereas the result for TCW Concentrated Value N is inconclusive. The reason for TCW Concentrated Value N not being in the simulated range can be due to the large number of constituents in the benchmark, i.e. n is high. As mentioned earlier, these circumstances combined with using randomized weights cause that the weights to become too small. In fact, some of the weights become so small that many of the constituents are practically zero. This no longer reflects realistic benchmark weightings, which drives the simulated AS range upwards. This is also shown in Figure 4.5. In addition, when the benchmark constituents become smaller, i.e. below 28 and 13 for TCW Concentrated Value N and Lannebo Sverige, the AS range increases, which reflects outcomes where the two funds are holding stocks outside of the benchmark and thus making the deviation greater in those stock positions[7].

Table 4.2: Test of Monte Carlo Model

	TCW Concentrated Value N (n=500)	Lannebo Sverige (n=30)
True Active Share	89.8% (q=28)	43.4% (q=13)
Simulation with randomized benchmark weights		
Maximum Active Share	96.7%	76.7%
Minimum Active Share	92.1%	34.3%
Mean Active Share	94.4%	57.4%

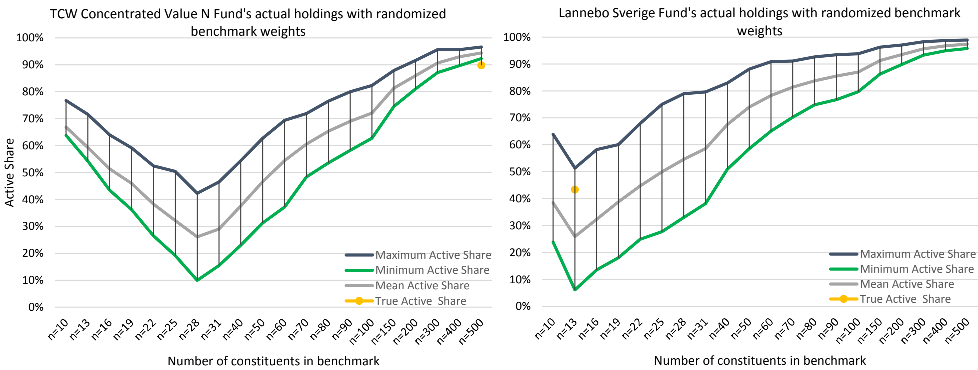
Note: True active share as of 31/12/2015.

Source: own contribution

In sum, the model is highly dependent on whether or not random weights serves as a sufficient proxy for benchmark weights. The test showed that estimation error occurs, when the benchmark reaches a large number of constituents, which causes the weights to become inaccurate compared to the real benchmark weights. Furthermore, there is a possibility that another estimation errors can occur if the benchmark consists of few large constituents that dominate the benchmark weightings. Despite the above, the model seems to be appropriate for identifying cut-off points. This can be the case if: 1) the fund only hold stocks that overlaps with the benchmark, and 2) the benchmark has a reasonable weight distribution combined with a reasonable number of constituents, e.g. between n=40 and n=100.

[7] The input values for Figure 4.5 can be found in Appendix B, Table B.3.

Figure 4.5: Simulated active share range for the two funds: TCW Concentrated Value N and Lannebo Sverige



Source: own contribution

4.6 Test of Robustness of Alternative Monte Carlo Model

This section tests an alternative model's applicability based on randomized fund portfolio weights. For this test, I resort to a simulation where I randomize the fund's portfolio weights whilst including the actual benchmark holdings. Thus, I repeal assumption 2 and 3. This implies that all funds ignore diversification, which does not comply with how fund managers do portfolio management in practice. The different setup works as another test of model robustness and thus tests if more accurate results can be achieved. The same two funds are used for the test, TCW Concentrated Value N, and Lannebo Sverige. The simulated AS range for the two funds is shown in Table 4.3 and plotted in Figure B.5, Appendix B[8]. Contrary to the previous test, the simulated AS range for the large benchmark has been lowered (90.02% - 93.1% from previously 92.1% - 96.7%), whereas for the small benchmark, the AS range has gone up (40.8% - 77.8% from previously 34.3% - 76.7%). This test also places Lannebo Sverige's true AS within the simulated AS range, while TCW Concentrated Value N's true AS gets closer to the simulated range, but remains outside. As opposed to the randomized benchmark weight test, Lannebo Sverige's true AS is in fact below the simulated AS mean, and therefore according to this test, the fund is no longer considered truly active.
Despite changing the setup from randomized benchmark weights to randomized fund portfolio weights, the simulated AS ranges came out similar to each other. As the

[8]The related input values for Figure B.5 can be found in Appendix B, Table B.4.

Table 4.3: Test of Randomized of Portfolio Weights

	TCW Concentrated Value N (n=500)	Lannebo Sverige (n=30)
True Active Share	89.8% (q=28)	43.4% (q=13)
Simulation with randomized portfolio weights		
Maximum Active Share	93.1%	77.8%
Minimum Active Share	90.02%	40.8%
Mean Active Share	90.5%	53.2%

Note: True active share as of 31/12/2015.

Source: own contribution

above model repeals assumption 2 and 3 stating funds seek to diversify portfolio positions, which is reflecting real practice, it is argued that the proper model approach is to randomize benchmark weights to simulate AS ranges, and not randomize portfolio holdings.

4.7 Conclusion

In terms of implications from applying the AS measure for funds and benchmarks with different characteristics, the analysis using the MC model has concluded that there are primary implications. In other words, the model indicated that a fund's AS is highly dependent and limited by two variables: 1) the fund's benchmark size, measured by number of constituents, and 2) the number of stocks held by the fund. Therefore, funds that invest in smaller markets and thus also have small benchmarks will not be able to achieve a relatively high AS. This is due to that the funds are constrained between obtaining a fully diversified portfolio and limited by a scarce supply of investable stocks. This prevents the fund from deviating significantly and therefore also reaching a high AS. For funds investing in smaller markets, one could prevent penalizing their level of active management by more fairly evaluating AS by comparing a fund's AS (preferably true AS) with the simulated mean AS. This can be done by cross-checking a fund's calculated AS with its simulated AS ranges to be determined from Table B.1 and B.2 in Appendix B.

CHAPTER 5
Characteristics of Funds with High Active Share

The purpose of this chapter is to address sub-question *b*:

- What are the characteristics of funds with a high active share?

Previous studies show that AS has been a good measure to identify various fund characteristics. For example, AQR Capital Management and Vanguard allude that funds with high AS tend to have high fees. Another example is that funds with high AS also tend to have high return dispersion, as found by Fidelity Investments[5][2][4]. This chapter seeks to determine similar characteristics of funds with high AS by examining AS's relationship with fund fees and fund excess returns. In addition, the chapter will empirically examine AS over time, and to test whether the variables from Chapter 4 tend have an impact on AS.

The chapter is comprised of six main sections, namely: 5.1) Approach; Description of the examined markets. 5.2) Active share over time; Development of AS for the sampled funds. 5.3) Impacts on active share; Examination of variables affecting AS through the use of Pearson's correlation estimates. 5.4) Active share against fees; Examination of funds with high AS and fees. 5.5) Active share and tracking error against excess returns; Examination of the two measure's ability to separately detect high performing funds. 5.6) Conclusion; Summary of the characteristics of funds with high AS.

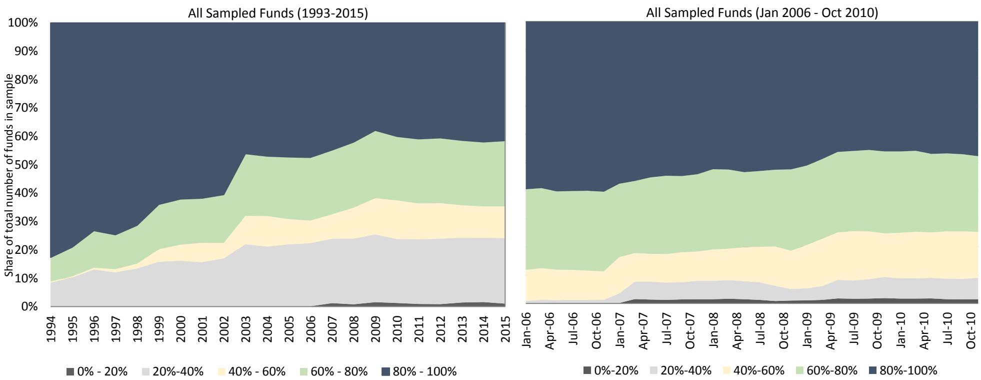
5.1 Approach

In order to accurately examine the different fund characteristics, three out of eight markets have been selected from the sample. The markets are World Markets, Small Efficient Markets, and Smallcap Markets. The three markets have been selected based on distinctive market characteristics as they vary in benchmark size and investment style. For instance, World Markets represent funds with larger benchmarks that are investing in largecap stocks. Small Efficient Markets, on the other hand, represent funds with smaller benchmarks, investing in small-, mid- and largecap stocks. Lastly, Smallcap Markets represent funds having a large benchmarks and investing in small-cap stocks. Additionally, in aims of examining each particular fund characteristic, Pearson's correlation estimates are performed on different variables to investigate their impact on AS.

5.2 Active Share Over Time

This section examines whether funds' AS are consistent or volatile over time. To illustrate this, Figure 5.1 plots the AS of the total sampled funds over the time period spanning from 1994-2015, alongside a truncated period from 2006-2010.

Figure 5.1: Active share over time - total sampled funds



Note: Sampled funds' active share sorted into quintiles. The LHS chart shows the annual active share, whereas the RHS chart shows quarterly active share.

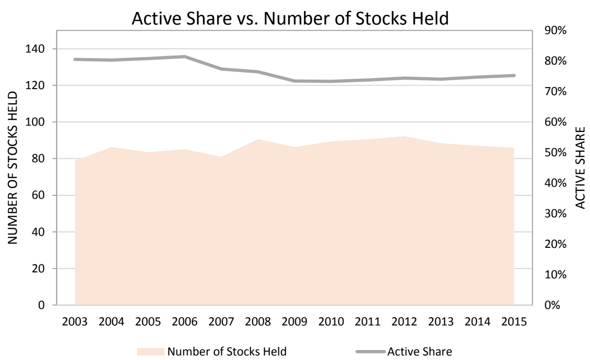
Source: own contribution

The AS chart for 1994-2015 time period illustrates that the supply of highly actively managed funds is diminishing, i.e. funds in the top quintile, 80-100%[1]. However, the second most actively managed funds, i.e. AS within the 60%-80% quintile, has doubled from 1994-2015. The remaining less actively managed funds with an AS within the range of 0%-60% have also become more wide-spread. Thus, in general funds are deviating less from their benchmark today than previously.
To examine how the sampled fund's AS react to volatile macroeconomic events, the chart on the right in Figure 5.1 shows a reduced time period focused prior to, during, and after the financial crisis. The chart depicts that highly active funds with an AS

[1]It should be noted that the density of sampled funds is relatively poor prior to 1997, with 214 funds in 1994 compared to 2,182 funds in 2015.

between 80-100% have become less active between 2007 and 2009. This is investigated further in Figure 5.2, which illustrates the sampled average AS against the average number of stocks held from the period 2003-2015[2]. The AS in this figure also shows that the average fund in the sample becomes less active. Additionally, when looking at the peak of the financial crisis, in 2007-2008, it is apparent that the average fund increases the number of stocks held. Increasing the number of stocks during volatile times could suggest two things: 1) highly active funds may not be completely diversified when financial markets are in stable economic conditions, and/or 2) funds are overdiversifying when financial markets are unstable to minimize the return gap to the benchmark and thus limiting the potential loss.
On a side note, the results from the period between 2007-2008 appear to potentially imply a negative relationship between AS and the number of stocks held. This relationship is in accordance with the Monte Carlo findings in Chapter 4 and will examined in further detail in section 5.2.

Figure 5.2: Active share vs. number of stocks held - total sampled funds



Note: Yearly average active share of all sampled funds vs. the yearly average number of stocks held by all sampled funds in the period 01/01/2003 - 01/01/2015.

Source: own contribution (fund data from Morningstar Direct, and inspiration from active share study by Morningstar 2016)

5.3 Impacts on Active Share

Chapter 4 and the previous section suggested that there may in fact be an empirical relationship between number of stocks held and AS. Based on the three selected markets, this section seeks to determine if the three variables, namely the number of stocks held, benchmark size, and cash position held, have an impact on AS.

[2] The time period has been reduced due to poor data coverage prior 2003.

According to the Monte Carlo Model in Chapter 4, a fund's AS is influenced by two variables, i.e. the fund's benchmark size measured by number of constituents, and the number of stocks held by the fund. A third variable that has not yet been discussed in this thesis is the cash position held by the fund. A positive cash position tends to have an impact on AS as a benchmark index only includes investable stocks. The cash position functions as an active bet and thus drives up the AS for the fund. Therefore, it is expected that all three variables have the following impacts on AS:

1. All other things held constant, a fund with many stocks will impact the AS value negatively, i.e. a negative correlation.
2. All other things held constant, a fund with a large cash position will impact the AS value positively, i.e. a positive correlation.
3. All other things held constant, a fund with a large benchmark with many constituents will impact the AS value positively, i.e. a positive correlation.

While these three variables may seem like irrelevant measures for fund performance, there is some empirical evidence that holding an appropriate number of stocks matter as a prerequisite for good performance. For example, Shawky and Smith (2005) define a fund's optimal number of stocks as a trade-off between diversification benefits and transaction costs. Thus, holding too few stocks will impose a greater risk of not being adequately diversified, as opposed to holding too many stocks, which is costly in terms of higher transaction costs[3]. Similarly, in regards to AS, it may also be the case that there is a relationship between a certain level of AS and good performance[4].

To examine whether the three variables have the expected impact on AS, they have been entered into a correlation matrix in Table 5.1. The table depicts the correlation between the three variables and AS, performed on the three different markets, within the period 01/01/2003 - 01/01/2015.

Table 5.1 shows that the variable regarding cash position held has a significant positive correlation with AS in small efficient markets (coefficient = 0.51***), while the correlation is relatively insignificant in the two other markets (coefficient = -0.20* and 0.07). In other words, there seems to be an empirical basis for the cash position held variable having a positive impact on AS in Small Efficient Markets, whereas it is inconclusive in the other two markets.
Table 5.1 also shows that the number of stocks held variable is negatively correlated with AS in two of the markets (coefficient = -0.59*** and -0.39***), whereas Smallcap

[3]However, the exact trade-off is undefined in the literature. Some suggest that one can achieve a fully diversified portfolio by investing in 10 randomly picked stocks, whereas others suggest around 30-40 stocks, and some even 100 stocks[44].

[4]At this stage, this question is indecisive, but will be tested in Chapter 7: The Performance on Different Groups of Active Management.

Table 5.1: The correlation between AS, number of stocks held, number of constituents, and cash held

	World Markets			**Small Efficient Markets**			**Smallcap Markets**		
	Active Share	Number of stocks held	Number of constituents in benchmark	Active Share	Number of stocks held	Number of constituents in benchmark	Active Share	Number of stocks held	Number of constituents in benchmark
Active Share									
Number of stocks held	-0.59***			-0.39***			0.74***		
Number of constituents in benchmark	-0.72***	0.41***		-0.82***	0.40***		-0.83***	-0.54***	
Cash position held	-0.20*	0.36***	0.25**	0.51***	-0.41***	-0.49***	0.07	0.00	-0.08

[a] Pearson's correlation estimates for three different markets, in the period 01/01/2003 - 01/01/2015.
[b] *, **, and *** indicate the 10%, 5%, and 1% significance level, respectively.
[c] Number of stocks held is expressed as the average number of stocks across all the funds, in each of the three markets. Number of constituents is expressed as the average number of constituents in all of the funds' benchmarks, in each of the three markets. Cash position held, equivalent to univensted capital, is expressed as an average percentage of the fund's TNA, in each of the three markets.

Source: own contribution

Markets show a significant positive correlation (coefficient = 0.74***). The explanation for the contradictory correlation in the three markets is ambiguous. While the previous Monte Carlo Model in Chapter 4 clearly outlined a positive relationship between AS and number of stocks held, this empirical correlation test shows that there has been no relationship in Smallcap Markets[5].
In terms of the benchmark size variable measured by the number of constituents, Table 5.1 does not show the expected positive correlation to AS in any of the selected markets. On the contrary, there is a significant negative relationship between AS and number of constituents (coefficient = -0.72***, -0.82*** and -0.83***). These coefficient estimates also conflict with the Monte Carlo Model findings in Chapter 4. The reason for the unexpected impact of number of constituents in benchmark on AS may be explained by funds in practice tend to invest in stocks that are not included in their benchmark. As previously mentioned, funds investing in stocks outside of their benchmark has the effect of undermining the number of constituents and thus causing a negative impact on AS. As it turns out in practice, funds investing in Small Efficient Markets, in particular, tend to place a large fraction of their portfolio outside their benchmark. This is particularly when the benchmarks are small in number of constituents and funds are thus unable to obtain a fully diversified portfolio.

Figure 5.3 depicts a case for funds investing in Small Efficient Markets. The upper

[5] The suggested relationship in Figure 5.2 between AS and number of stocks held does not seem to exists empirically.

part of Figure 5.3 shows a comparison between the average number of stocks held and the average number of constituents in the benchmarks. The lower part of Figure 5.3 plots the yearly distribution of number of stocks held, sorted into quartiles, and the average number of constituents for the benchmarks. The figure demonstrates that the average fund in Small Efficient Markets tends to exceed the number of stocks relative to the benchmark, which inevitably causes a higher inflated AS for these funds. The figure also illustrates the average number of funds in each quartile. The lowest quartile, consisting of 124 funds, is the only comprised of funds holding a number of stocks that does not exceed the average benchmark. The funds in the 2nd, 3nd, and highest quartile all held a higher number of stocks than their benchmark. This suggests that funds with smaller benchmarks that typically are unable to achieve a relatively high AS compared to funds with larger benchmarks, empirically tend to achieve a high AS by having a misleading benchmark. Funds having misleading benchmarks is a general concern when computing AS and is discussed in more detail in Chapter 10.

5.4 Active Share Against Fees

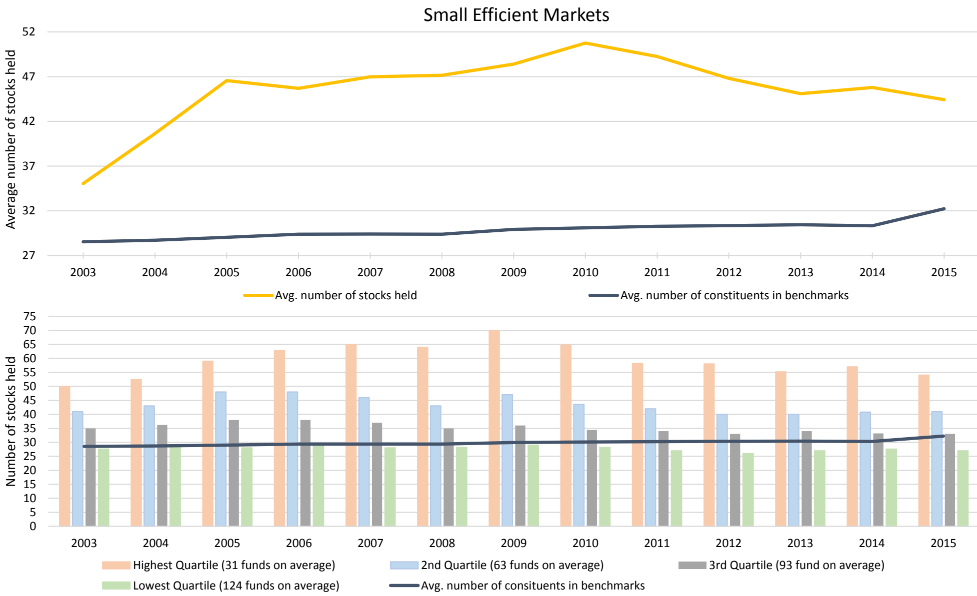
This section aims to determine whether funds with higher AS are associated with higher fee characteristics. While several studies, e.g. from AQR Capital and Vanguard, disprove AS and TE's capability to identify outperforming funds, the consensus is that AS is useful for measuring whether an active fund is justifying its active fees. Figure 5.4 plots AS as a function of the annual expense ratios in the three different markets. Each dot represents a fund's five year average AS with its corresponding five year average expense ratio. The three scatter plots indicate that funds with high AS embody higher annual fees ($R^2 > 0.07$ in all markets). Thus, funds with high AS values are more likely to charge higher fees than funds with low AS values are.
However, an alternative, and yet an arguably more accurate approach to examine fees of active funds, is to look at the active part of the portfolio[6]. In terms of active fund fees, a study from Morningstar (2016) defines an active fund by two components, i.e. the active part itself (active share) and the passive part invested in the benchmark (1-active share). Ideally, the latter part of any active fund should equal the proportional costs of an ETF with a similar investment area[8]. Hence, by stripping the fees of the passive part, one would arrive at a more accurate fee estimate of an active fund (based on AS). This fee estimate corresponds to the 'expense ratio unit per AS' (abbreviated ERUAS) and is calculated as,

$$ERUAS = \frac{ER_{fund,i} - [ETF_{ER} * (1 - AS_{fund,i})]}{AS_{fund,i}} \tag{5.1}$$

Where, $ER_{fund,i}$ is the expense ratio for fund i, ETF_{ER} is the corresponding ETF's expense ratio for each market, and $AS_{fund,i}$, is the AS of fund i.

[6] Inspired by Morningstar's latest active share study in 2016[8].

Figure 5.3: A case for funds investing in Small Efficient Markets - number of stocks held and benchmark constituents



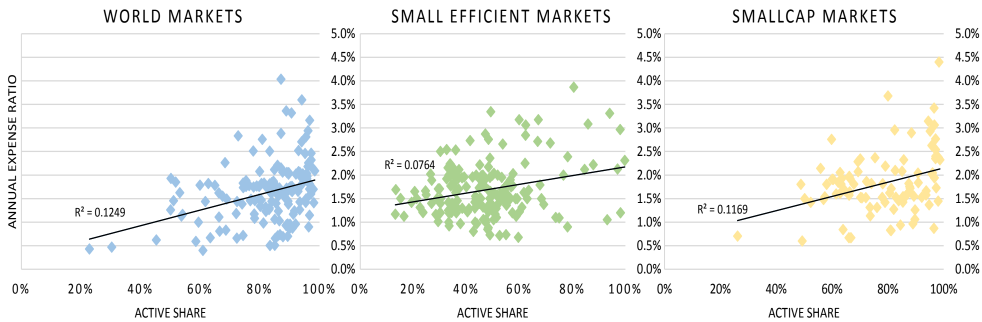
Note: The Figure shows funds investing in Small Efficient Markets in the period 01/01/2003 - 01/01/2015. The upper part of the figure shows the number of stocks held by the average fund and the number of constituents in the average benchmark. The lower part shows the distribution of number of stocks held divided into quartiles. The median of the average number of stocks by the funds investing in Small Efficient Markets is 39, whereas the median for the average number of constituents in the benchmark is 28.

Source: own contribution (fund data from Morningstar Direct)

To compute the expense ratio unit per AS, three ETF's have been selected as proxies for the passive part of the portfolio in the three different markets. The three selected ETF's are: Vanguard Total World Stock ETF, Vanguard FTSE All-World ex-US Sm-Cp ETF, and Global X FTSE Nordic Region ETF. These are proxies for World Markets, Small Efficient Markets, and Smallcap Markets, respectively. The ETF's corresponding five-year average expense ratios are 21, 28 and 50 basis points[7].
Figure 5.5 plots AS as a function of expense ratio per unit of AS for the three markets. Contrary to Figure 5.4, Figure 5.5 shows that when stripping the passive fee part (1-active share) from the expense ratio, funds with high AS empirically no longer implies higher fees in World Markets and Small Efficient Markets. In other words, the expense ratio for a unit of AS is rather constant, which means that the magnitude of fees is

[7]Source: Morningstar Direct.

Figure 5.4: Expense ratio vs. active share - three different markets

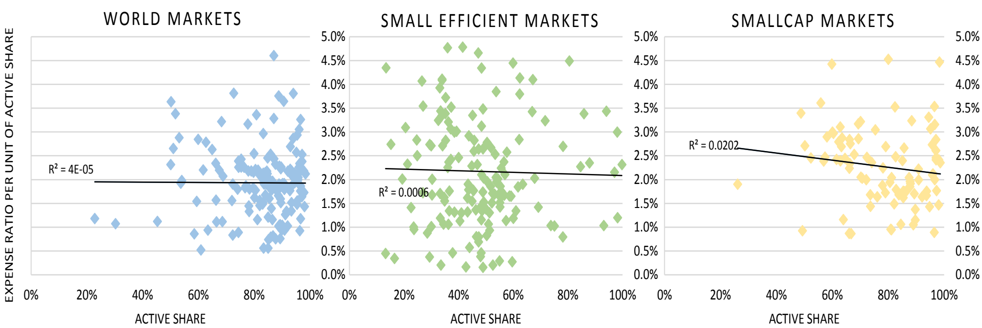


Note: Average annual active share and average annual expense ratio for the time period, 01/01/2010 - 01/01/2015.

Source: own contribution (fund data from Morningstar Direct)

independent of the level of AS. However, in Smallcap Markets, fees are not entirely independent of the level of the funds' AS. Here, the relationship between AS and the expense ratio per unit of AS is slightly negative ($R^2 = 0.02$), which indicates that funds with a low AS are more likely to charge a higher expense ratio per unit of AS than funds with a high AS are. In conclusion, the empirical examination demonstrates that high fees do not necessarily imply a high fund AS.

Figure 5.5: Active share vs. expense ratio per unit of active share - three different markets



Note: Active share and expense ratio unit per active share, for the time period, 01/01/2010 - 01/01/2015.

Source: own contribution (fund data from Morningstar Direct)

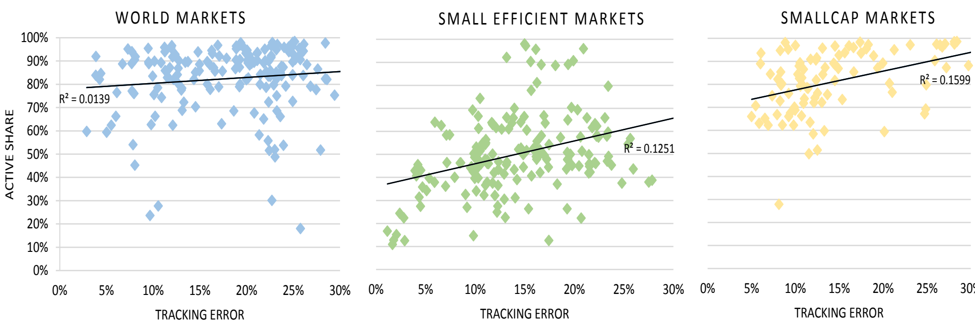
5.5 Active Share and Tracking Error Against Excess Returns

Previous findings by Petajisto (2013) affirmed that combining the two active measures, AS and TE, could help identify funds with abnormal returns. The following section examines the empirical correlation between the two measures and attempts to determine whether AS and TE can be used as separate stand-alone indicators to detect high performing funds.

5.5.1 Active Share and Tracking Error

Since AS and TE are both measures of active management, it is expected that there exist some degree of relationship between the two. However, the two measures are not expected to be highly related since they are defined to capture two distinctly different types of active management. Figure 5.6 plots the relationship for the three different markets. As expected the figure shows a small but positive relationship between the two active measures in all markets. Hence, the two measures are somewhat related, which may seem intuitive considering the purpose of identifying stock picking with AS and systematic behavior of TE.

Figure 5.6: Tracking error vs. active share - three different markets



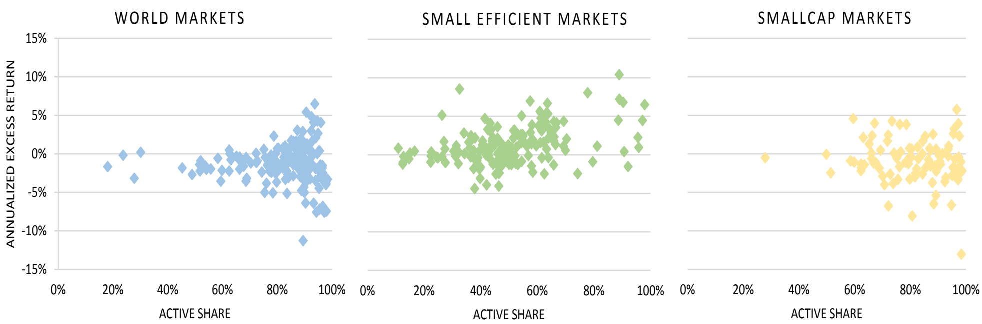
Note: Average tracking error and active share for the time period, 28/02/1994 - 31/05/2015.

Source: own contribution (fund data from Morningstar Direct)

5.5.2 Active Share and Excess Return

To properly examine AS' ability to identify high performing stocks, the empirical relationship between AS and excess returns has been plotted in Figure 5.7 using average annualized net excess returns and yearly average AS. Figure 5.7 shows no clear relationship between a fund's level of AS and excess returns. Although it could look like there is a positive tendency in Small Efficient Markets, the vast number of dots in all three plots illustrate no clear relationship between a fund's level of AS and excess returns[8]. Figure 5.7 also shows that funds with a high AS tend to have higher return dispersion compared to funds with a low AS. This is in line with the study from Fidelity Investments carried out in 2014.

Figure 5.7: Active share vs. excess returns - on three different markets



Note: The returns are average annualized excess returns over the examined time period of 28/02/1994 - 31/05/2015, for the entire sampled funds. Active share is time series weighted in the period.

Source: own contribution (fund data from Morningstar Direct)

5.5.3 Tracking Error and Excess Return

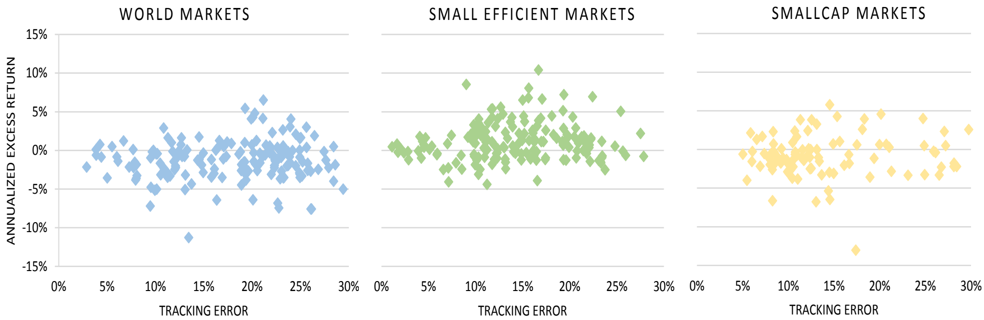
When looking at TE's relation to excess return in Figure 5.8 it appears that, contrary to AS, the annualized excess return is independent from the level of TE, i.e. the return dispersion is rather constant. This indicate that funds with a high TE are as likely to experience a high dispersion in fund returns as to funds with a small TE.

5.6 Conclusion

When financial markets are unstable, the average active fund seems to increase the number of stocks held and thus become less active.
While the Monte Carlo Model findings in Chapter 4 indicated that the two variables, number of stocks held and benchmark size, had an impact on AS, there were no empirical basis to conclude similar findings in practice for the three examined markets.

[8] It should be noted that this relationship is not statistically significant

Figure 5.8: Tracking error vs. excess returns - on three different markets



Note: The returns are average annualized excess returns over the examined time period of 28/02/1994 - 31/05/2015, for the entire sampled funds. Tracking error is time series weighted in the period.

Source: own contribution (fund data from Morningstar Direct)

The reason behind the contrary findings can possibly be attributed to the fact that funds tend to hold stocks that are not included in the benchmark, which results in artificially high inflated AS values. There was, however, some empirical evidence that cash position held has a positive impact on AS.

Additionally, it was found that funds with high AS typically have higher fees, particularly whilst considering both the active and the passive part of a fund's portfolio. However, when examining the cost per unit of AS and separating the active part of the portfolio from the passive, high fees were independent of the level of AS. This was the case in all three markets that all had a more or less constant 'expense ratio per unit of AS'.

As expected, it was also shown that there exists a relationship between AS and TE. Lastly, it was confirmed that funds with high AS tend to be associated with higher dispersion in fund returns, whereas there was no such relationship for funds with a high TE.

CHAPTER 6

Categorizing Groups of Active Management

The purpose of this chapter is to address sub-question *c*:

- To what degree are the sampled funds actively managed?

While Chapter 5 exclusively examined characteristics of funds with high AS, the objective now is to assess the degree of active management for the sampled funds by applying the two measures, AS and TE, as a means of categorizing the funds into different groups. The funds will be separated into five groups of active management. As previously mentioned, applying both measures is an accurate manner of assessing the level of active management for a fund. Yet, the output of AS may vary from TE while assessing funds in markets with different characteristics. Therefore, the sampled funds are further divided, specifically according to the eight market areas with different characteristics, as this may help explain why AS values deviate from TE values for funds in certain markets. The chapter is divided into the following two sections: 6.1) Distribution of active share and tracking error, and 6.2) Distribution of the five groups.

6.1 Distribution of Active Share and Tracking Error

This section outlines an overview of the total sampled funds' AS and TE. Table 6.1 depicts a snapshot for the distribution of AS and TE values of the total sample. As in section 5.4, the distribution shows that most funds have both high AS and TE. This somewhat implies that the two measures are positively correlated, which seems intuitive as they are both proxies for active management. The majority of the sampled funds cluster between AS values of 60-100%, and TE values of 4-12%. Unexpectedly, the sample also shows several funds, likely to be outliers, that have extreme opposite AS and TE values. In the south-east corner of the table, there are funds with high TE values and low AS values, while the north-west corner of the table contain funds with low TE values and high AS values. For many of these funds, the extreme nature may be explained by wrongly assigned benchmarks causing unlikely opposite values.

Table 6.1: The distribution of active share and tracking error for the sampled funds

Active Share (%)	Tracking error (%)								
	0-2	2-4	4-6	6-8	8-10	10-12	12-14	>14	Total #funds
90-100	5	47	92	107	111	109	63	88	622
80-90	2	42	104	70	59	66	34	57	434
70-80	2	56	74	54	33	43	18	61	341
60-70	3	47	44	32	24	32	9	49	240
50-60	1	40	29	13	15	16	9	29	152
40-50	2	21	16	18	11	15	8	23	114
30-40	2	20	15	12	7	19	2	11	88
20-30	1	7	16	9	3	4	2	8	50
10-20	0	7	3	1	0	1	0	2	14
0-10	1	14	35	15	12	11	9	30	127
Total #funds	19	301	428	331	275	316	154	358	**2,182**

Note: Snapshot of monthly active share and tracking error per 31/05/2015.

Source: own contribution (inspiration from Petajisto (2013))

6.2 Distribution of the Five Groups

This section illustrates and comments on the sample distribution of the five groups of active management across the eight markets. Table 6.2 and Figure B.9 in Appendix B show how the sampled funds have been categorized into the five different active management groups and divided into the eight markets[1]. The categorization of funds into the five groups of active management is based on relative AS and TE values. Hence, all markets have funds represented in each group as shown in Table 6.2. As mentioned in Chapter 4, the use of absolute values would not be appropriate as it would penalize funds who invest in smaller markets. In other words, using absolute AS and TE values for a fund with AS of 49% would result in a label as Closet Index fund across seven of the eight markets with higher average AS. However, this would be considered active in the Small Efficient Markets with a mean AS of 44.84%. Moderately active funds represent the group of funds with the highest distribution of funds across all markets (about 60%), which has the widest range in terms of both AS and TE. The group of funds with the second and third highest distribution across the eight markets are Stock Picking funds and Closet Index funds (about 17% and 16% respectively). Despite the use of relative AS and TE values, the presence of Closet Index funds is relatively high. The second lowest distribution of funds is Concentrated funds, whereas the lowest is Factor Betting funds. Concentrated funds and Factor Betting funds represent a relatively low number of funds in all markets. Thus, in the following performance evaluation in Chapter 7, it should be noted that these two groups are more dependent on the returns of the individual fund, compared to the group of Moderately Active funds. Additionally, Table 6.2 depicts the mean AS and TE values. Here, both AS and TE mean values differ amongst the different markets. The difference in the AS values is highest among World Markets, whereas Small

[1] The sample size has been reduced to 1,526 funds from 2,182 funds. 656 funds have been excluded as they did not have any of the eight markets as their investment area.

Efficient Markets has the lowest. As previously touched upon, and in coherence with the theory, this can be explained by AS being dependent on the number of constituents in the benchmark, where the World Markets have on average 1,281 constituents and Small Efficient Markets bear 25 constituents[2]. The TE difference is also relatively significant amongst the various markets, with Small Inefficient Markets having the highest average TE and US Markets having the lowest. Yet, in this case, the two markets have on average 71 and 75 constituents. The disparity has thus empirically proven that TE is independent of benchmark sizes. In conclusion, this ultimately suggests that TE is a more appropriate measure for assessing the level of active management for funds across markets with different benchmark sizes.

Table 6.2: Active management groups across markets

	US Markets		Asia Markets		EU Markets		World Markets	
Mean Active Share	80.31%		71.85%		69.21%		81.47	
Mean Tracking error	5.23%		9.47%		8.82%		11.06%	
(Relative grouping)	Number of funds	Share of the market	Number of funds	Share of the market	Number of funds	Share of the market	Number of funds	Share of the market
Stock Pickers	72	11%	9	17%	31	17%	19	13%
Concentrated	73	11%	2	4%	7	4%	11	8%
Moderately Active	390	58%	1	58%	108	59%	82	58%
Factor Betters	8	1%	30	2%	5	3%	4	3%
Closet Indexers	124	19%	10	19%	30	17%	25	18%
Total	667	100%	52	100%	181	100%	141	100%

	Large Inefficient Markets		Small Inefficient Markets		Small Efficient Markets		Small Cap Markets	
Mean Active Share	73.53%		54.05%		44.84%		77.30%	
Mean Tracking Error	8.43%		14.41%		7.39%		10.19%	
(Relative grouping)	Number of funds	Share of the market	Number of funds	Share of the market	Number of funds	Share of the market	Number of funds	Share of the market
Stock Pickers	17	18%	23	26%	27	13%	10	12%
Concentrated	2	2%	1	1%	14	7%	3	4%
Moderately Active	58	60%	60	69%	126	58%	53	63%
Factor Betters	4	4%	2	2%	5	2%	1	1%
Closet Indexers	15	16%	3	3%	43	20%	17	20%
Total	97	100%	89	100%	215	100%	84	100%

Note: Snapshot of the five groups of active management across the eight different markets per 31/05/2015. A graphical illustration of the table can be found in Appendix B, Figure B.9.

Source: own contribution

[2]The number of constituents for each market can be found in Appendix A, Table A.1.

CHAPTER 7
The Performance on Different Groups of Active Management

This chapter addresses sub-questions *d* and *e*:

- What is the performance of the different groups of active management in the examined markets?
- What are the factors/variables explaining benchmark-adjusted fund returns across the different groups of active management funds?

According to CAPM and the efficient market hypothesis no fund should be able to actively and consistently generate a superior risk-adjusted return. However, the previous findings of Fama, French, and Carhart (1992, 1993, 2014 and 1995) show that certain markets have anomalies suggesting that financial markets may be inefficient. These findings have served to inspire the two purposes of this chapter. The first purpose is to examine fund performance of the five different groups of active management, particularly through the use of two risk-adjusted performance measures, namely Jensen's alpha and Carhart's four-factor model. The performance of the different groups of funds will be examined across eight markets. This will be carried out to ultimately determine if a certain group of funds is able to detect and exploit market anomalies by delivering abnormal returns. The second purpose is to explain what factors are influencing the fund returns of the different active management groups.

This chapter is structured in eight sections, broken down as follows: 7.1) Approach; Description of the models used for evaluating fund performance. 7.2) The performance of the full sample; Performance evaluation of all sampled funds on a total basis and in the five groups. 7.3) The performance of Closet Index funds. 7.4) The performance of Factor Betting funds. 7.5) The performance of Moderately Active funds. 7.6) The performance of Concentrated funds. 7.7) The performance of Stock Picking funds. 7.8) Conclusion; Sum up of the performance evaluation of the different groups of active management in the different markets, assisted by a risk analysis.

7.1 Approach

To determine whether funds are significantly outperforming (or underperforming) their benchmarks, on a risk-adjusted basis, I test the null hypothesis, H_0: $\alpha = 0$, through numerous regression models in the period 28/02/1994 - 31/05/2015. In all of the regression models, the gross and net benchmark-adjusted fund returns are treated as the dependent variable. To obtain the risk-adjusted fund returns, I apply Jensen's alpha and Carhart's four-factor model, which historically have both been proven to be good at explaining returns. In terms of the model relevance, I only conclude on performance models that have a sufficiently high R^2 (coefficient of determination) and an adjusted R^2 combined with a statistically significant alpha ($\approx$model intercept). To achieve somewhat useful models, I consider a sufficient R^2 and an adjusted R^2 to be 1% and above[1]. To measure the statistical significance of the intercept, i.e. alpha, and the independent variables, I provide a t-statistic for every estimate with a corresponding significance level[2]. The following sections will separately examine the performance of the overall sample, and subsequently, the five groups with different level of active management across the eight markets. The next sections will present thorough evaluations of the performance of the most significant model outputs are presented, whereas the full and detailed model output is presented in Appendix C, as indicated in the footnotes.

7.2 The Performance of the Overall Sample

Before examining the fund performance across the eight markets, I run two performance models for the entire 2,182 sampled active funds.
The first model evaluates the overall performance of active funds without sorting the funds into the different groups that separate active management versus their benchmarks. According to Jensen's alpha and Carhart's four-factor model, I find that active funds neither under- nor outperform their benchmark significantly[3].

In the second performance model, the funds have been sorted into the different groups of active management in order to evaluate whether funds with a certain level of active management tend to generate a significant alpha[4]. This performance model shows that the lowest and the highest active group of funds, i.e. Closet Index funds and Stock Picking funds, tend to beat their benchmark before fees. Table 7.1 displays the gross return of the two groups of funds for the entire sample in Carhart's four-factor model. Closet indexers delivered a positive significant alpha of 0.1% ($\approx$ 1.2%

[1]Although, a regression model with an adjusted R^2 of 1% is far from being considered a 'good' model.

[2]A t-statistic of around |2| indicate a statistical significant variable, which corresponds to a probability of less than 5%[11].

[3]The regression outputs for the test can be found in Appendix C, Table C.1, and C.2.

[4]A complete overview of the regression outputs for all groups of active management across the sample can be found in Appendix C, Table C.3, C.4, C.5, and C.6.

on an annual basis), while Stock Picking funds also had a positive significant alpha in Carhart's four-factor model of 0.02% (≈ 2.4% annually). The outperformance by Closet Index funds indicate that these funds are able to justify a strategy of low levels of active management by successfully selecting outperforming stocks in the few active positions that outweighs the passive part. Similarly, the outperformance by Stock Picking funds indicate that these funds justify a strategy of high levels of active management by generating a larger return in the active positions. While it is noted that both of these groups of funds generate a positive alpha it is not of significant magnitude when taken the excess fees charged by active funds into account.

Table 7.1: All sampled funds - Closet Index and Stock Picking funds - Carhart's four-factor model

	Benchmark Adjusted Gross Returns	
	Closet Indexers	Stock Pickers
MKT	0.005	0.003
	$t = 0.697$	$t = 0.132$
SMB	−0.013	0.075
	$t = -0.915$	$t = 1.635$
HML	−0.029	0.111
	$t = -2.306^{**}$	$t = 2.669^{***}$
MOM	0.001	0.028
	$t = 0.160$	$t = 1.146$
Alpha	0.001	0.002
	$t = 2.671^{***}$	$t = 2.278^{**}$
Observations	253	228
R^2	0.029	0.040
Adjusted R^2	0.013	0.023
Note:		*p<0.1; **p<0.05; ***p<0.01
		Estimates are in monthly percentage points

Source: own contribution (produced in R)

The factors in Jensen's alpha and Carhart's four-factor model provide useful indications regarding the possible causes of the variation in fund returns. The interpretation of a factor is that for any percentage point change in a factor will cause a change in the fund return (assuming that the remaining factors in the model are held constant)[11]. In Carhart's four-factor model, the returns of Closet Index funds and Stock Picking funds are explained by the HML factor, which is statistically significant with estimates of -0.029 and 0.111, respectively. Thus, for each percentage point increase in HML strategy, the return of Closet Index funds drops by -2.9%, whereas the return of Stock Picking funds increases by 11.1% (monthly). The significant HML factors indicate that both groups of funds are sensitive to how growth and value stocks perform (i.e. low book-to-market, and high book-to-market stocks). Closet Index funds have a negative loading of the HML factor, which may suggest that these funds tend to hold more growth stocks. Stock Picking funds have a positive loading of the HML factor, which seems to suggest the opposite of the previous claim and that these funds, to a larger extent, tend to hold value stocks. In order to obtain a more detailed performance evaluation of fund's level of active management, the following sections will examine the performance on different markets.

7.3 The Performance of Closet Index Funds

When examining Closet Index funds in the eight different markets, only funds investing in Large Inefficient Markets and US Markets showed significant alpha, after fees, according to the four-factor model[5]. Table 7.2 shows the model output of the two groups' net returns. In Table 7.2, it can be observed that Closet Index funds in both Large Inefficient Markets and US Markets underperformed their benchmark by -0.2% ($\approx -2.4\%$ annually) and -0.1% ($\approx -1.2\%$ annually). Thus, while the total sampled Closet Index funds outperformed their benchmark before fees, Closet Index funds investing in Small Inefficient Markets and US Markets consistently underperformed after fees. These results are in accordance with Petajisto (2013), who discovered that US domiciled Closet Index funds, before fees, tend to match the returns of the benchmark, while significantly underperforming their benchmarks after fees.

The factors explaining the returns of the two markets are SMB (significant at the 5% level). Closet Index funds investing in Inefficient Markets have a positive SMB loading, which suggests that these funds hold many smallcap stocks, whereas a negative loading for Closet Index funds investing in US Markets suggests the opposite. Lastly, the HML factor is significant negative at the 1% level for Closet Index funds investing in US Markets, which indicate that these funds are more exposed to growth stocks than value stocks. Hence, the returns of Closet Index funds in US Markets tend to be negatively impacted when value stocks are performing well.

The general perception of Closet Index funds is that they rarely justify their excess fees by delivering abnormal return, or even the market return. The performance evaluation proved to support this perception. In fact, the results indicate that, on average, investing in Closet Index funds in Large Inefficient Markets and US Markets tend to be value destroying.

7.4 The Performance of Factor Betting Funds

Similar to Closet Index funds, and according to Jensen's alpha and Carhart's four-factor model, the consensus regarding Factor Betting funds is that they underperform their benchmark net of fees. The performance findings are illustrated in Table 7.3[6]. This is also in line with previous findings by Petajisto (2013), which suggest that it is not optimal to invest in funds, which pursue a strategy based on factor timing. However, before fees, the average Factor Betting fund investing in Smallcap Markets

[5]The regression outputs for Closet Index funds in each of the eight markets can be found in Appendix C, Table C.7, C.8, C.9, and C.10.

[6]The regression output for Factor Betting funds in each of the eight markets can be found in Appendix C, Table C.11, C.12, C.13, and C.14.

Table 7.2: Closet Index funds - Carhart's four-factor model

	Benchmark Adjusted Net Returns	
	Large Ineff. Net	US Net
MKT	0.006	0.007
	$t = 0.696$	$t = 1.014$
SMB	0.050	−0.023
	$t = 2.222^{**}$	$t = -2.286^{**}$
HML	0.002	−0.025
	$t = 0.077$	$t = -2.622^{***}$
MOM	0.017	0.003
	$t = 1.357$	$t = 0.439$
Alpha	−0.002	−0.001
	$t = -4.063^{***}$	$t = -1.944^{*}$
Observations	148	253
R^2	0.051	0.042
Adjusted R^2	0.025	0.027
Note:		*p<0.1; **p<0.05; ***p<0.01
		Estimates are in monthly percentage points

Source: own contribution (produced in R)

outperformed their benchmark considerably. On a monthly basis the average small-cap Factor Betting fund delivered an excess return of 0.6% relative to the average benchmark ($\approx$ 7.2% annually).

Table 7.3: Factor Betting funds - Jensen's alpha and Carhart's four-factor model

	Benchmark Adjusted Gross and Net Returns			
	Smallcap Gross	World Net	World Net	US Net
MKT	−0.092	0.052	0.065	−0.003
	$t = -1.781^{*}$	$t = 1.948^{*}$	$t = 2.122^{**}$	$t = -0.123$
SMB			0.022	0.027
			$t = 0.246$	$t = 0.581$
HML			−0.116	−0.126
			$t = -1.348$	$t = -3.210^{***}$
MOM			−0.005	−0.032
			$t = -0.138$	$t = -1.237$
Alpha	0.006	−0.003	−0.003	−0.002
	$t = 2.122^{**}$	$t = -2.485^{**}$	$t = -2.386^{**}$	$t = -1.736^{*}$
Observations	74	112	112	179
R^2	0.042	0.033	0.051	0.082
Adjusted R^2	0.029	0.025	0.016	0.061
Note:				*p<0.1; **p<0.05; ***p<0.01
				Estimates are in monthly percentage points

Source: own contribution (produced in R)

However, not all of the traditional regression model assumptions for Factor Betting funds are met. According to the linearity and autocorrelation assumption[7], all four

[7] Linearity plots and test for autocorrelation can be found in Appendix D.

markets in Table 7.3 have weak model diagnostics. Thus, the usefulness and quality of these results is not high and will therefore not be further analyzed.

7.5 The Performance of Moderately Active Funds

The performance evaluation of Moderately Active funds showed significant findings for funds investing in Small- and Large Inefficient Markets. The models are displayed in Table 7.4[8]. For Moderately Active funds investing in Small Inefficient Markets, Jensen's alpha and Carhart's four-factor model show that the funds tend to outperform their benchmarks before fees, while the model results after fees are insignificant. The abnormal performance could possibly be attributed to weak market inefficiency, which these funds are able to exploit. However, in Large Inefficient Markets, Moderately Active funds tend to underperform after fees by -0.1% ($\approx -1.2\%$ annually). Thus, these two findings contradict with each other and therefore prevent anything conclusive to be said about the performance of Moderately Active funds in inefficient markets.

Table 7.4: Moderately Active funds - Jensen's alpha and Carhart's four-factor model

	Benchmark Adjusted Gross and Net Returns		
	Small Ineff. Gross	Small Ineff. Gross	Large Ineff. Net
MKT	0.047	0.049	0.006
	$t = 2.173^{**}$	$t = 2.069^{**}$	$t = 0.499$
SMB		0.104	0.028
		$t = 1.667^{*}$	$t = 0.889$
HML		0.052	0.005
		$t = 0.709$	$t = 0.133$
MOM		0.002	0.039
		$t = 0.045$	$t = 2.263^{**}$
Alpha	0.003	0.003	-0.001
	$t = 2.717^{***}$	$t = 2.320^{**}$	$t = -1.731^{*}$
Observations	148	148	148
R^2	0.031	0.051	0.045
Adjusted R^2	0.025	0.025	0.018
Note:			*p<0.1; **p<0.05; ***p<0.01
			Estimates are in monthly percentage points

Source: own contribution (produced in R)

There are two significant factors explaining the fund returns for Moderately Active funds in Small Inefficient Markets, and those are the MKT and the SMB factors[9]. Both factors have a positive loading, which indicates that a price change in any of these factors will impact the funds' return positively. For Moderately Active funds

[8] The regression outputs for Moderately Active funds in each of the eight markets can be found in Appendix C, Table C.15, C.16, C.17, and C.18.

[9] Small Inefficient Markets are characterized as inefficient markets with smaller benchmarks and is not to be confused with smallcap stocks, which would make it irrelevant to include the SMB factor.

investing in Large Inefficient Markets, the MOM factor seems to be the only factor influencing fund returns positively.

7.6 The Performance of Concentrated Funds

For Concentrated funds, the only market that delivered a significant alpha before fees was funds investing in World Markets with a considerable abnormal return of 0.5% ($\approx$ 6% annually) (Table 7.5)[10]. However, after fees, the performance of this group of funds was statistically insignificant. While the excess return of 6% annually exceed most of any active fund's fees, it is not a direct indicator of significant outperformance after fees.

Despite a sufficient explanatory power for both models, no factors were found that, significantly contributed to the variation in fund returns. This can be due to relatively low values of R^2 and adjusted R^2, illustrated in Table 7.5.

Table 7.5: Concentrated funds - Jensen's alpha and Carhart's four-factor model

	Benchmark Adjusted Gross Returns	
	World Gross	World Gross
MKT	0.082	0.045
	$t = 1.616$	$t = 0.811$
SMB		0.228
		$t = 1.465$
HML		0.068
		$t = 0.436$
MOM		-0.085
		$t = -1.200$
Alpha	0.005	0.005
	$t = 1.948^{*}$	$t = 1.950^{*}$
Observations	138	138
R^2	0.019	0.045
Adjusted R^2	0.012	0.016
Note:		*p<0.1; **p<0.05; ***p<0.01
		Estimates are in monthly percentage points

Source: own contribution (produced in R)

7.7 The Performance of Stock Picking Funds

According to Jensen's alpha and Carhart's four-factor model in Table 7.6, Stock Picking funds only showed significant performance in Smallcap Markets, before fees[11].

[10] The regression outputs for Concentrated funds in each of the eight markets can be found in Appendix C, Table C.19, C.20, C.21, and C.22.

[11] The regression outputs for Stock Picking funds in each of the eight markets can be found in Appendix C, Table C.23, C.24, C.25, and C.26.

Smallcap Stock Picking funds outperformed their benchmark by 0.2% per month (≈ 2.4% annually), while the performance after fees was statistically insignificant. This result is not entirely in line with previous findings by Petajisto (2013), who found that Stock Pickers in the US outperform their benchmark even after fees.
After referring to the existing literature, it seems to come as no surprise that funds investing in smallcap stocks do well. For instance, Fama and French (1992, 1993) find a strong negative relationship between stock sizes and returns, i.e. smaller firms have greater returns on average than larger firms. This is explained by small firms having greater risk because of more sensitive prospects[12], e.g. through economic downturns, which consequently is rewarded by higher returns[10].

Table 7.6: Stock Picking funds - Jensen's alpha and Carhart's four-factor model (reduced)

	Benchmark Adjusted Gross Returns	
	Smallcap Gross	Smallcap Gross
MKT	-0.050	-0.041
	$t = -1.961^{*}$	$t = -1.479$
HML		-0.052
		$t = -0.663$
MOM		0.013
		$t = 0.382$
Alpha	0.002	0.002
	$t = 1.941^{*}$	$t = 1.868^{*}$
Observations	148	148
R^2	0.026	0.030
Adjusted R^2	0.019	0.010
Note:		*p<0.1; **p<0.05; ***p<0.01
		Estimates are in monthly percentage points

Source: own contribution (produced in R)

Table 7.6 shows that there is only one significant factor explaining a fraction of the fund return, and that is the MKT factor with a negative load. Thus, for each percentage point increase in the market, the returns of Stock Picking smallcap funds drop by -5% (monthly). The table only includes three factors. The SMB is left out since Smallcap Markets are categorized as funds solely investing in smallcap stocks.

7.8 Conclusion

The performance findings revealed reasonable evidence indicating that a fund's level of active management does in fact matter. The performance evaluation for the total sampled funds showed that Closet Index funds and Stock Picking funds generated

[12] Small firms also embody greater informational asymmetry for investors than large firms typically do, which smallcap investors should enjoy a risk premium for[10].

a superior benchmark-adjusted return before fees. This indicate these two groups of funds are able to select outperforming stocks in their active part of the portfolio, which outweighs the passive part. Additionally, the performance models showed that in five out of eight markets, there was a statistical significant performance difference between the funds and their benchmarks in four out of five of the active management groups from the period 28/02/1994 - 31/05/2015. Table 7.7 summarizes the findings.

Table 7.7: Summary of markets with significant alpha

Markets	Closet Indexers		Factor Betters		Moderately Active		Concentrated		Stock Pickers	
	Gross	Net	Gross	Net	Gross	Net	Gross	Net	Gross	Net
All Sampled Funds	***								**	
US		*								
Large Ineff.		***				*				
Small Ineff.					***					
World							*			
Smallcap									*	
Asia										
EU										
Small Eff.										

[a] Green and red indicate statistically significant out- and underperformance, respectively.
[b] *, **, *** indicate a statistically significant alpha at the 10%, 5%, and 1% level, respectively.
[c] Blank indicate an insignificant performance model.
[d] The table does not distinguish between which of the two performance measures, Jensen's alpha or Carhart's four-factor model, is significant.

Source: own contribution

For the eight markets, the performance evaluation of less actively managed funds, Closet Index- and Moderately Active funds, did not support any superior risk-adjusted performance. In fact, the two groups of funds tend to consistently underperform their benchmark whilst adjusting for fees. On the other hand, the performance evaluation of highly actively managed funds derived slightly more compelling results. Concentrated- and Stock Picking funds have outperformed their benchmark consistently before adjusting for fees, while the consistent outperformance was not statistically significant after fees. Therefore, it is not definitive whether or not highly active funds are able to generate superior risk-adjusted returns for investors, while taking the fees into consideration. In conclusion this also means that the performance evaluation showed that AS and TE cannot necessarily be used as measures to identify funds with abnormal returns. However, the two active measures indicate that they may be used to identify less actively managed funds that, in some markets, consistently underperform net of fees.

In terms of explaining fund returns, the factors gathered from Jensen's alpha and Carhart's four-factor model that are meant to give reason for the fund's performance, seem to vary greatly. Yet, the results indicated that the SMB and HML factors generally explained most of the funds' benchmark-adjusted returns. There may be other specific factors or characteristics for funds that generate abnormal returns versus funds that underperform. In Chapter 8 another model will applied to test this further.

7.8.1 Risk Analysis of the Different Groups of Active Management

Chapter 5 disclosed that funds investing in certain investment areas with a higher level of active management, e.g. World Markets, had a higher return dispersion in terms of AS. This subsection more comprehensively analyzes whether a high level of active management is associated with a greater market risk, based on sorting funds by both AS and TE. The following will investigate the risk of the different groups of active management using two risk measures, Value at Risk (VaR, eq. 3.1) and expected shortfall (ES, eq. 3.2).

For both risk measures, I assume fund returns to be normally distributed, which according to previous model diagnostic tests, is a reasonable assumption[13]. In this risk analysis, VaR corresponds to the 5th percentile return and can be interpreted as the maximum potential loss[14] (or gain) in 95% of the cases. For instance, the maximum potential loss of a stock position with a value of $1.000.000 and a VaR of 5% is $50.000, given a 95% confidence level. Or, to put it in another way, $50.000 would be the minimum potential loss in 5% of the cases[45].
ES is generally assumed to be a better approximation for risk. Contrary to VaR, ES measures the average potential loss in the 5th percentile, and thus give a higher loss estimate compared to VaR. Therefore, ES is expected to be a greater than VaR[11].
Table 7.8 illustrates the total sampled fund's VaR and ES for the five groups of active management. As expected, the table shows that ES for all fund groups are greater than VaR. In terms of risk levels, Closet Index funds have the the lowest potential loss (VaR=0.0081, ES=0.0099), given a confidence interval of 95%, whereas Concentrated funds has the highest potential loss (VaR=0.0322, ES=0.0392). Factor Betting funds has the second lowest potential loss (VaR=0.0145, ES=0.0174), and Stock Picking funds has the second highest potential loss (VaR=0.0273, ES=0.0335). Finally, Moderately Active funds have a medium potential loss relative to the other fund groups (VaR=0.0156, ES=0.0194).
Table 7.8 shows a positive relationship between risk and levels of active management, as it appears that the more a fund deviates from its benchmark, in terms of AS and TE, the higher the potential loss.
While the performance evaluation in section 7.3 indicated that Closet Index funds in some markets tend to underperform consistently, it is also shown that they have the lowest potential loss amongst the five groups. This may be explained by the fact that Closet Index funds characteristically tend to deviate very little from their chosen

[13]The VaR and the ES methodology are explained in more detail in section 3.1.6.
[14]Or expected maximum loss.

Table 7.8: Risk measures of the five different groups of active management

	All Sampled Funds				
	Closet Indexers	Factor Betters	Moderately Active	Concentrated	Stock Pickers
VaR	0.0081	0.0145	0.0156	0.0322	0.0273
ES	0.0099	0.0179	0.0194	0.0392	0.0335

[a] VaR = Value at Risk, and ES = Expected Shortfall.
[b] VaR and ES are computed at a 95% confidence level.
Source: own contribution

benchmark, which in terms of risk, gives Closet Index funds an advantage of having a lower potential loss.
Table 7.8 shows that Factor Betting funds are associated with a higher potential loss compared to Closet Index funds. This seems intuitive since Factor Betting funds are characterized as being less diversified while having a higher exposure to systematic factors (e.g. investing solely in specific sectors)[37]. These characteristics result in higher potential losses compared to Closet Index funds.
Moderately active funds showed a higher potential loss than Closet Index funds and Factor Betting funds, possibly because the group tends to be more active (medium AS and medium TE).
Among the five groups of active management, Concentrated funds showed the highest potential loss. This could potentially be explained by the fact that Concentrated funds are characterized as the most active group (high AS and high TE), and thus deviates most from their benchmark, which consequently results in a higher downside risk.
Stock picking funds, which are slightly less active than Concentrated funds (high AS but lower TE), had the second highest potential loss, which also indicates that the level of active management matters for the maximum potential loss.

In sum, according to VaR and ES, the level of active management is related to risk. This means that a highly active fund is more likely to suffer a greater potential loss, whereas a less actively managed fund is more likely to have a lower potential loss. Hence, the two active measures, AS and TE, are ultimately relevant when identifying groups of funds with the highest and lowest potential loss. This result provides useful information to some investors that are selecting between actively managed funds. All other things held constant, a risk averse investor should steer away from high actively managed funds to avoid the possibility of high losses and instead choose less actively managed funds.

CHAPTER 8

Explaining Fund Returns Using Alternative Regression Models

This chapter will continue to address sub-question *e*:

- What are the factors/variables explaining benchmark-adjusted fund returns across the different groups of active management funds?

Chapter 7 disclosed that the MKT, SMB and HML factors often had statistically significant impact on fund returns for different levels of active management across the eight markets. However, the loadings were both positive and negative. Therefore, this chapter further investigates the variation in benchmark-adjusted fund returns using a comprehensive correlation analysis followed by Jensen's alpha with included self-chosen fund-specific variables.

The chapter is structured in five sections. 8.1) Approach; Description of the applied approach. 8.2) The correlation between fund-specific variables and fund returns; Investigation of fund-specific variables and benchmark-adjusted fund returns. 8.3) A closer look at highly active funds in Smallcap Markets; Test of fund-specific variables for Stock Picking funds investing in Smallcap Markets. 8.4) Causality problems of fund-specific variables; Description of possible reverse causality of the fund-specific variables. 8.5) Conclusion; Sums up the variables explaining the variation in benchmark-adjusted fund returns.

8.1 Approach

Similar to Chapter 7, the approach of this chapter is to apply an alternative regression model, assisted by a Pearson's correlation analysis of fund-specific variables, for the purpose of explaining benchmark-adjusted fund returns. Contrary to Chapter 7, the purpose is not to determine whether funds are significantly outperforming or underperforming using fund-specific variables, but more specifically on what is causing

the change in returns. Thus, in this chapter the intercept of the alternative regression models is not to be interpreted as alpha.
Instead of including risk factors from Cahart's four-factor model, the following will apply self-chosen independent variables[1]. These are: fund size, expense ratio, portfolio turnover, total number of stocks held, top 10 holdings (%), cash position held (%), average market capitalization, and manager tenure. The methodology of these variables are described in more detail in section 3.2.1.

8.2 The Correlation Between Fund-specific Variables and Fund Returns

Table 8.1 depicts a comprehensive correlation matrix of the chosen fund-specific variables and the benchmark-adjusted fund returns (gross and net of fees) for the total sampled funds. The variables have been chosen based on possible relationship to fund returns. While the intuition for some variables being related to fund returns may be higher than others, the majority of variables have frequently been examined in the literature[2]. Looking at Table 8.1, it shows three significant coefficient estimates to fund returns. Logically, benchmark-adjusted gross returns are highly correlated with benchmark-adjusted net returns. Among the fund-specific variables, portfolio turnover and number of stocks held are the only two significant variables (at a 10% significance level), which have a relationship with fund returns (both gross and net of fees). The coefficient of portfolio turnover is positive with an estimate of 0.18, which indicate that the frequency in terms of how often a fund trades is affecting the fund returns positively. Number of stocks held has a negative estimate of -0.16, which indicate that holding too many stock positions is not beneficial. Since many of the variables have an insignificant impact on returns, only three variables will be used to investigate the benchmark-adjusted returns further in an alternative regression model in Section 8.3.

In addition to fund-specific variables explaining returns, the matrix also shows the relationships between the other selected variables. In terms of fund size it is correlated with the number of stocks, which mean that large funds tend to carry a high number of stocks, e.g. indicating that larger funds may want to increase number of holdings to avoid liquidity issues, whereas smaller funds tend to hold less stocks[3]. Also in terms of fund size, it is shown that there is no economies of scale as there is no significant negative correlation to expense ratio. In regards to fees, there is a

[1] All of which have been screened in the Morningstar Direct database.

[2] For example Ferreira et al. (2004) examine fund size, fees, and manger tenure's relation to fund returns, whereas Shawky and Smith (2004) examine the relationship between number of stocks held, average market capitalization, cash position held, top 10 holdings, and portfolio turnover[15][44].

[3] Similar relationship is also found by Shawky and Smith (2005).

significant correlation to fund manager tenure indicating that experienced managers are cheaper[4].

Table 8.1: Correlation matrix of fund-specific variables - total sampled funds

	Benchmark Adj. Gross Return	Benchmark Adj. Net Return	Fund Size	Expense Ratio	Portfolio Turnover	Number of Stocks Held	Top 10 Holdings (%)	Cash Position Held	Average Market Capitalization
Benchmark Adj. Gross Return									
Benchmark Adj. Net Return	0.93***								
Fund Size	0.02	0.01							
Expense Ratio	-0.07	-0.07	-0.06						
Portfolio Turnover	0.18*	0.21**	0.20**	-0.15*					
Number of Stocks Held	-0.16*	-0.14*	0.16*	-0.02	0.06				
Top 10 Holdings (%)	0.05	0.03	-0.21*	0.03	-0.09	-0.16*			
Cash Position Held	0.01	0.01	0.06	-0.01	0.05	-0.34***	0.04		
Average Market Capitalization	0.10	0.12	-0.31***	0.12	-0.20**	-0.45***	0.14*	0.25***	
Manager Tenure	-0.02	-0.03	0.65***	-0.14*	0.55***	0.37***	-0.20**	-0.13	-0.74***

[a] Pearson's correlation estimates for fund-specific variables 28/02/1994 - 31/05/2015.
[b] *, **, and *** indicate the 10%, 5%, and 1% significance level, respectively.
[c] All fund-specific variables have been screened in the Morningstar Direct database.

Source: own contribution (fund-specific variables from Morningstar Direct)

8.3 A Closer Look at Highly Active Funds in Smallcap Markets

This section examines the fund-specific variables' impact on returns of one group of funds with a high level of active management in an alternative regression model. Based on the performance evaluation, Stock Picking funds investing in Smallcap Markets tend to generate an abnormal benchmark-adjusted return of 2.4% annually[5]. before fees. For this reason this group of funds is investigated further in regards to relevant fund-specific variables.
The three specific variables applied are: i) Manager tenure, ii) Portfolio turnover, and iii) Fund-specific size. As Stock Picking funds are highly active in terms of many active bets, i.e. a high AS, manager tenure and portfolio turnover are chosen as potentially

[4] At a significance level of 10%, although the relevance of this relationship is not great since manager tenure is uncorrelated with fund returns.
[5] According to Carhart's four-factor model in Chapter 6, Table 7.6.

relevant variables for the group. Furthermore, fund-specific size is included to control for any constraints a fund may have due to its size in some of the smaller markets. Manager tenure, expressed in years, is used as a proxy for stock selection skills. The idea behind manager tenure is that the longer the manager has tenured the more experienced she has gained. Hence, the purpose of including manager tenure is to examine whether an experienced manager adds value, expressed by a statistically significant relationship between manager tenure and fund performance. Portfolio turnover, expressed in percentage, is used as a proxy for how active a fund is in terms of frequency of trades. Including portfolio turnover can potential indicate whether a fund follows a buy and hold strategy (e.g. a turnover below 30%) or an investment strategy that involves considerable buying and selling (e.g. a turnover above 100%), and if any of them correlate with fund performance[32]. Fund-specific size expressed as a fund's TNA is used to examine whether the size of a fund may hinder, or improve, the performance of highly active funds. Table 8.2 depicts the regression output of Jensen's alpha model along with the mentioned three variables. From the regression output it is observed that all of the variables, i.e. fund-specific size, portfolio turnover and manager tenure are statistically significant at a minimum significance level of 10%.

Table 8.2: Explaining fund returns: Stock Picking funds - Additional variables

	Benchmark Adjusted Returns	
	Smallcap Gross Return	Smallcap Net Return
MKT	−0.038	−0.038
	$t = -1.503$	$t = -1.506$
Size	−0.006	−0.006
	$t = -2.690^{***}$	$t = -2.625^{**}$
Portfolio Turnover	−0.056	−0.056
	$t = -2.604^{**}$	$t = -2.594^{**}$
Manager Tenure	0.001	0.001
	$t = 1.923^{*}$	$t = 2.042^{**}$
Intercept	0.109	0.103
	$t = 2.437^{**}$	$t = 2.320^{**}$
Observations	101	101
R^2	0.166	0.168
Adjusted R^2	0.131	0.133
Note:		*p<0.1; **p<0.05; ***p<0.01
		Estimates are in monthly percentage points

Source: own contribution (produced in R)

Fund-specific size turns out to be negatively correlated with fund performance, which suggests that large funds investing in smallcap stocks have a negative influence on returns. The inverse relationship between fund size and performance has empirical support from Chen et al. (2004) among other, who find that the performance of individual smallcap funds erodes as their size increases[17]. A possible reason to smallcap fund size's decreasing return to scale may be related to poor liquidity, which smallcap stocks often are characterized by.

Manager tenure, or manager skill, is positively related to performance both gross and net of return (although a small estimate). This could indicate that fund managers possess some skill in selecting stocks, however this empirical output does not suggest whether managers can generate superior risk-adjusted returns. Historically, this is a heavily discussed topic among academicians, where for example, Kacperczyk et al. (2014) find that managers are superior during economic booms and recessions, whereas Berk and Green (2002) find it pointless to chase performance[46][47].
Portfolio turnover shows to be positively related to returns both gross and net of fees for Smallcap Markets, whereas there was a negative correlation in Table 8.1 in section 8.2. This could indicate that it is favorable to pursue a buy and hold strategy rather than an investment style of frequently buying and selling stocks. Arguably, it is not considered optimal to trade too frequently as it will drive up the transaction costs, which ultimately will diminish the fund's net return.

8.3.1 Reduced Time Period

As a robustness check, a similar regression model for Stock Picking funds investing in Smallcap Markets for a shorter time period has been conducted. The time period has been set to 2007-2014 in order to examine the performance of smallcap funds during an economic downturn and recovery. To prevent the model from lacking explanatory power no less than 86 return observations have been included. The regression output for the shortened time period is illustrated in Table 8.3. When reducing the time period, it becomes clear that fund size and portfolio turnover still have a negative significant impact on fund returns, whereas manager tenure has become insignificant.

8.4 Causality Problems of Fund-specific Variables

When testing the variation in returns one should consider whether the causality between the fund-specific variables are logical. For example, while manager tenure is used as a proxy for a manager's stock selection skills, it may have a reverse causality to fund returns[6].
It could be the case that when a fund is performing well there is lack of incentive for the fund management to switch portfolio managers. In this case, the manager tenure becomes dependent on fund return rather than the opposite intended relationship.
Another case could be a situation where there exists dependence between two independent variables (multicollinearity). This could be a positive relationship between manager tenure and market return. For instance, imagining a fund manager who takes on higher risk will not be replaced unless the market takes a significant beat. Thus, market return and manager tenure would be proxies for the same effect on fund returns.

[6] And possibly other fund-specific variables as well.

Table 8.3: Explaining fund returns: Stock Picking funds - Additional variables (truncated time period)

	Benchmark Adjusted Returns (2007-2014)	
	Smallcap Gross Return	Smallcap Net Return
MKT	−0.043	−0.043
	$t = -1.537$	$t = -1.548$
Size	−0.001	−0.001
	$t = -2.448^{**}$	$t = -2.417^{**}$
Portfolio Turnover	−0.058	−0.058
	$t = -2.435^{**}$	$t = -2.415^{**}$
Manager Tenure	0.0001	0.0001
	$t = 0.973$	$t = 1.043$
Intercept	0.148	0.143
	$t = 2.250^{**}$	$t = 2.186^{**}$
Observations	86	86
R^2	0.190	0.192
Adjusted R^2	0.150	0.152
Note:		*p<0.1; **p<0.05; ***p<0.01
		Estimates are in monthly percentage points

Source: own contribution (produced in R)

Presumably there exist similar reverse relationships between both portfolio turnover and fund returns, as well as for fund-specific size and fund returns. Thus, there is basis for criticizing the model with fund-specific variables as there is a possibility of reverse causality among the variables. On the contrary, Jensen's alpha and Carhart's four-factor model are based on risk factors and the reverse causality is therefore not considered to be an issue in those models.

8.5 Conclusion

In conclusion, it was initially found for the entire sample of funds that only two of the variables, namely portfolio turnover and number of stocks held, had a significant correlation, and thus impact, on benchmark-adjusted fund returns (positive and negative respectively). Looking specifically at Stock Picking funds investing in Smallcap Markets, it was found that three variables, namely fund size, manager tenure and portfolio turnover, had a significant correlation to fund returns (negative, positive and negative respectively). Yet, in the reduced time period, manager tenure was insignificant in the alternative regression model. In other words there has been found no empirical evidence that certain fund-specific variables can explain the variation in benchmark-adjusted fund returns (portfolio turnover positive in whole sample and negative in Smallcap Markets).

CHAPTER 9

Conclusion

The following concludes first on the five (a-e) sub-questions and secondly, and finally, on the overall problem statement.
In terms of sub-question a "What are the implications for applying the active share measure for funds and benchmarks with different characteristics?", it was found, through a simulation in a Monte Carlo Model, that different benchmark characteristics have implications on funds' AS. The model showed that a fund's active share is highly dependent and potentially limited by two variables: 1) the fund's benchmark size, measured by number of constituents, and 2) the number of stocks held by the fund. In practice, this means that funds with smaller benchmarks aiming for a high level of diversification is likely not able to achieve a relatively high AS and vice versa. This finding is furthermore relevant as active funds with smaller benchmarks are often questioned and criticized for not being active enough using the AS measure and threshold of 60% by Petajisto (2013). In other words, there may be limitations with the AS measure and threshold for funds with certain benchmark characteristics. In terms of alternative approach, taking benchmark characteristics into account, max-, min- and mean- AS values were simulated varying the two variables, number of constituents in benchmark and number of stocks held. The simulation showed that the possibility of reaching AS varies significantly depending on the variables, including the mean AS. Following Petajisto's logic (2013) of characterizing a fund with an AS above the mean, the simulated mean values could be a more appropriate way to set AS threshold levels and thus get a more fair estimate of the level of active management. Additionally, one can improve the accuracy of the AS measure by ignoring fund's stock positions that are not part of the benchmark, and thus get even closer to 'the true active share'.

In terms of sub-question b "What are the characteristics of funds with high active share?", an empirical study was made on 2,182 funds. Initially, the two variables addressed in the previous section, benchmark size and number of stocks held, were tested on the sample. In contrast to the simulated output, the empirical test showed the opposite relationship between high AS and the two variables. Thus, there was found a relationship between small benchmarks and high AS, and a high number of stocks held was somewhat related to a high AS. A potential reason explaining the contradicting findings could be that funds tend to hold stocks that are not included in the benchmark, which results in artificially high inflated AS values.
In addition to sub-question b, two fund characteristics often related to active funds were also tested empirically; fund fees and fund excess returns. In terms of fund fees,

it was found that funds with high AS have higher fees when considering both the active and the passive part of a fund's portfolio. However, separating the active part of the portfolio from the passive part, examining the cost per unit of AS, there were no relationship between funds with high AS and fund fees. In practice, this indicates that funds with high AS do not necessarily charge additional fees for providing a higher level of active management. In terms of fund excess returns, it was found that funds with high AS tend to have higher dispersion in fund excess returns.

In Chapter 6 on sub-question *c* "To what degree are the sampled funds actively managed?" the sampled funds were categorized relatively and according to the five groups of active management for later purpose in following chapters. The majority of the funds had an AS value of 60-100%, and TE values of 4-12%. In terms of the five groups, most funds belonged to the Moderately Active group, accounting for approximately 60% in all of the eight markets. The second and third highest groups of funds were Closet Index- and Stock Picking funds, which accounted for about 17% and 16%, whereas Factor Betting- and Concentrated funds held the remaining shares.

On sub-question *d* "What is the performance of the different groups of active management in the examined markets?", the performance evaluation of the overall sample showed that the Closet Index funds and Stock Picking funds had superior benchmark-adjusted performance before fees in the period 28/02/1994 - 31/05/2015. This indicates that the two groups of funds are able to consistently select outperforming stocks in their active part of the portfolio, which outweighs the passive part, and in other words mean that investors should invest in funds pursuing either a very low- or a very high level of active management. However, in terms of performance after fees, there was no significant benchmark-adjusted performance for funds in any of the five groups, including the two above mentioned.
The evaluation of performance of funds in different markets were ambiguous for funds with low vs. high level of active management and performance before vs. after fees. For low level of active management in terms of Closet Index funds and Factor Betting funds, the results were insignificant before fees. On the contrary, the results after fees were significant for Closet Index funds in US and Large Inefficient Markets, which consistently underperformed in the period. For the funds with a high level of active management, the evaluation showed significant results for Stock Picking and Concentrated funds in Smallcap and World Markets, consistently outperforming their benchmarks before fees, whereas the results were insignificant after fees. In practice, the ultimate assessment of fund performance is based on returns after fees. As the performance evaluation showed no significant positive relationship between level of active management and performance after fees, it is likely that the level of active management cannot be used for investors to identify high performing funds. On the other hand, the evaluation did show that investors can use AS and TE to determine the level of active management and thus identify less actively managed funds (Closet Index funds) that are consistently underperforming their benchmarks after fees.
In addition to the performance evaluation, a risk analysis of funds in the five different

groups was conducted. In parallel to the positive relationship between funds with high AS and high return dispersion covered in Chapter 5, the risk analysis showed a similar relationship when considering both AS and TE combined. This means a highly active fund is more likely to suffer a greater potential loss than a less actively managed fund.

On sub-question *e* ”What are the factors/variables explaining benchmark-adjusted fund returns across the different groups of active management?”, a range of fund-specific variables were used to try explain the fund returns in the sample. The initial test involved using Jensen’s alpha and Carhart’s four-factor model factors and showed insignificant results on the whole sample, and significant but ambiguous results for the tested group Stock Picking funds in the one tested market Smallcap Markets. For the further selected and tested fund-specific variables, the results on the overall sample showed a significant correlation between the two variables, portfolio turnover and number of stocks, and fund returns (positive and negative respectively). However, the specific test on Smallcap Markets revealed a contradicting negative correlation between portfolio turnover and fund returns. In other words, the results indicate that fund-specific variables cannot be used to explain fund returns for funds with different levels of active management in different markets.

As an overall conclusion and response to the problem statement ”To what degree can the two active measures be used to determine the relationship between high fund performance and the level of active management?” AS and TE have been found to be somewhat decent measures for determining the level of active management for funds. Yet, the more detailed categorization of funds according to level of active management and the performance evaluation of funds within each of the groups in different markets, showed that investors cannot use the measures to identify funds with significant and consistently high performance.

9.1 Future Research

In practice the AS measure is occasionally biased upwards by funds having misplaced benchmarks, i.e. funds investing in stocks that are not included in their benchmark. Consequently, funds can be falsely characterized with a too high level of active management. This is not accounted for in the thesis, but the ’true active share’ could potentially be found by excluding fund investments outside of the benchmark and thus base the analysis of AS solely on stocks part of the benchmarks. This approach may yield different findings.

A suggestion for future research in terms of performance measures could be to apply the newer and more comprehensive five-factor model by Fama and French (2014) in order to determine the risk-adjusted fund returns, which are found to have a higher explanatory power for the variation in returns.

CHAPTER 10

Discussion

The following discussion is divided into two sections. The purpose of the first section is to relate the findings from the thesis on the limitations using the two measures, particularly the AS thresholds, to determine the level of active management together with how the measures are used in practice in the investment community. Moreover, the objective is to comment on how one could account for the limitation in order to determine a more accurate level of active management. The purpose of the second section is to cast a light on reasons for why the level of active management, despite accounting for certain benchmark characteristics when using AS and TE, may still not represent the 'true level of active share'. While the inaccurate level of active management is driven by the methodology in section one, the sources for inaccuracy in section two is driven by specific fund actions.

10.1 Accounting for Benchmark Characteristics in Practice

The following touches upon the implementation of the two measures, AS and TE, in the investment community in Europe as well as discusses whether the measures in practice are used properly to characterize funds in terms of levels of active management. Since the introduction of AS and TE, the measures have become widely used in practice by the investment community to determine whether the level of active management in active funds justify their fees. The reason for the wide use is, as previously found, that the two measures combined is a good way to identify Closet Index funds, whom increasingly have a reputation of being value destroying as well as considered expensive index funds. In particular, the financial agencies in the European countries have adopted the measures as a way to increase transparency and protection for investors. Lately and listed in the following, this has led to a range of accusations against asset managers in Europe.
In 2013, the Norwegian Financial Supervisory Authority (FSA) published a report addressing this issue based on the two active measures. The Norwegian FSA specifically accused one of the country's biggest asset managers, DNB Norge, for not adequately deviating from a passive index strategy and thus not justifying their excess fees[48]. The same year, the Danish FSA published a similar but more comprehensive market report of 188 Danish actively listed equity funds. The report concluded that 56 out

of the 188 Danish funds had characteristics of being Closet Index funds according to the two measures, and therefore did not follow the promised active strategy listed in the fund prospectus'[49].
In 2014, the investment community in Sweden took investigation of Closet Index funds to the next level. The Swedish Shareholder's Association filed a class-action lawsuit against two funds managed by Swedbank Robur, part of Sweden's biggest bank, for being mis-sold Closet Index funds [1][50][51].
In 2016, the European Securities and Markets Authority (ESMA) published the latest market outlook report on the matter. The ESMA alluded that 5-15% of 2,600 actively managed European domiciled funds were potentially Closet Index funds[52].
In comparison, earlier findings in the thesis revealed that about 17% of the 2,182 sampled funds were categorized as Closet Index funds as of 31/05/2015. In addition to identifying Closet Index funds as in the above mentioned situations, the thesis confirms that some Closet Index funds in fact have underperformed consistently compared to their benchmarks after adjusting for fees and have thus not justified their fees as often argued. The performance findings are likely to explain the popularity of the two measures with investors in terms of identifying and avoiding less actively managed funds in the mutual fund selection process.
However, the thesis concluded that using the two measures and particularly AS has a potential limitation that suggest the measures should be used with precaution in practice. As earlier mentioned, the potential limitation is related to AS' dependence on benchmark size and number of stocks held by the fund to determine level of active management, and ultimately the applied 60% threshold by Petajisto's (2013) used to categorize a fund. Originally, the 60% threshold was defined in the US market with larger benchmarks. Yet, in markets with certain characteristics, the determined level of active management and assigned group may not be fair. For example in Europe, as the previously mentioned reports were based on, many country specific benchmarks consist of few constituents, which is likely to result in falsely low levels of AS well below the 60% threshold and thus yield and inaccurate picture of the level of active management and grouping of funds. In practice, some financial agencies do seem to acknowledge this limitation, but few seem to have identified a corrective assessment method and reevaluated the cut-off point, e.g. as reported by the Danish FSA in 2013[49].

A wrong categorization in terms of level of active management can be very problematic for a fund. For example it can lead to negative implications such as fines and fund outflows[53]. Fund outflows, i.e. lost assets under management, and thus less fund income in terms of fees is particularly a very negative potential consequence. For example, when Swedish Stockholder Association filed a lawsuit against Swedbank, Morningstar estimated Swedish domiciled ETF's to have received an unusual positive fund inflows compared to actively managed funds from 2013-2016. The shift

[1] The Swedish Shareholder's Association demanded 7 billion Swedish kroner in refund for excess fees to their investors for the last 10 years.

in demand of index funds relative to active funds could indicate that investors have reacted on the episode and increasingly become better at identifying Closet Index funds among active funds as well as more aware of active funds not justifying their fees ($4.4 and $2.1 billion respectively)[54].

Overall, the above suggests that the current way of applying the two measures, AS and TE, is useful for certain benchmarks, but also, that some benchmarks require adjustments of the AS threshold when determining the level of active management. The above furthermore suggests that the investment community should adopt this modified approach, when assessing funds in particularly smaller markets as the consequences of a wrong categorization can influence a fund in a potentially very negative manner.

10.2 Funds Manipulating Active Share

In addition to making sure that the methodology for determining the level of active management is right and take into account potential relevant benchmark characteristics, the investor also needs to be aware of ways that the fund intentionally or unintentionally influence AS. While one of the assumptions for the Monte Carlo Model in Chapter 4 was that a fund's primary objective is to maximize returns by only selecting undervalued stocks, it is in practice, as discussed in section 10.1, likely to be in the interest of the fund manager to achieve a sufficiently high AS to avoid being considered a Closet Index fund. This section discusses five ways in which the AS measure can be manipulated by funds to achieve a higher level of active management.

One way of manipulating AS, pointed out by the CFA Institute[55], is by holding different securities of the same stock such as American Depositary Receipts (ADR's) and/or different share classes[2]. A benchmark index rarely includes multiple share classes of the same stock, which can enable a fund manager to deviate a stock position by 100% when selecting a share class that is not included in the benchmark.
A second way to manipulate AS, also pointed out by the CFA Institute, is to hold ETF's and thus replace a funds exposure to a certain sector in the passive part of the portfolio. Holding ETF's would prevent a fund manager from directly holding the underlying ETF holdings and would thus impact the AS significantly as benchmarks do not include ETF's.
A third way to manipulate AS, also mentioned earlier in the thesis, is the cash position held. As benchmark indices do not include cash positions it would increase a fund's AS. Presumably many funds hold cash for liquidity reasons while there may be others.
A fourth way to manipulate AS could be to initiate short selling positions, which would cause a fund's AS to deviate significantly.

[2]Funds presumably hold ADR's to hedge their currency exposure, whereas there may be other reasons for a fund to hold different share classes.

A fifth way and perhaps the most common one for a fund to manipulate AS, is fund managers selecting an incorrect benchmark. A fund with an incorrect benchmark has the same effect on AS as short positions and means that stocks outside of the benchmark will deviate by 100%. A numerical example of the manipulating of AS is shown in Appendix A, Table A.2. Ideally, a benchmark should reflect the fund's investment strategy and the investment area as listed in the fund prospectus, but as briefly mentioned in Chapter 3, an active fund manager has the mandate and may have the incentive to select an inaccurate benchmark to look better in terms of performance[24]. As this is typically a concern for investors when assessing active funds, they should carefully consider the validity of the fund's benchmark when applying the two measures, AS and TE, to determine the level of active management.

While the above situations are relatively common and can mislead investors in terms of level of active management, there remains limited ways for investors and analysts to recognize such manipulated measures. The takeaway on this aspect is therefore that investors should be aware of these pitfalls when considering the level of active management for funds.

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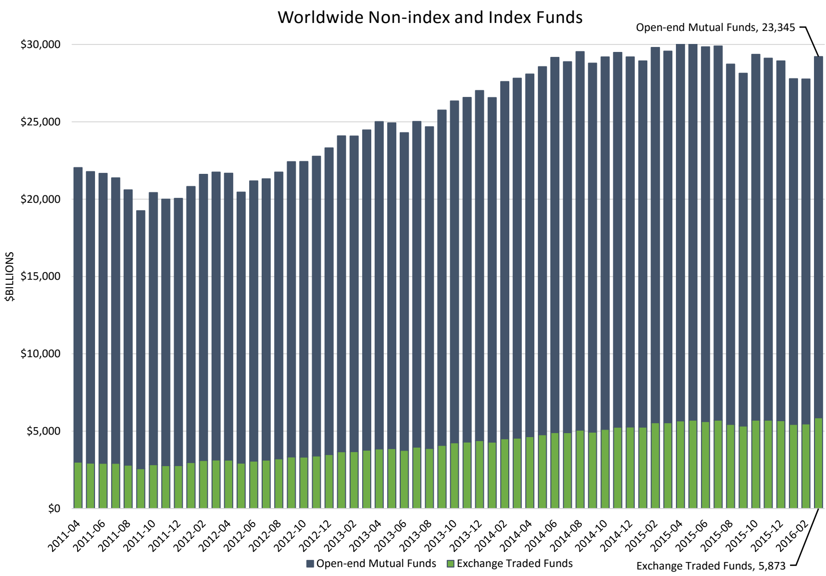
APPENDIX A

Appendix A

This appendix contain tables and figures related to Chapter 3, Data and Methodology.

Figure A.1: Global mutual fund market



Note: Figure shows the global fund flows sorted between active and passively managed funds.

Source: Morningstar Direct - Fund flows

Table A.1: Market subsambles and their included benchmarks

US Markets		
Benchmark	#Funds in benchmark	#Constituents in benchmark
S&P 500 TR USD	639	500
Russell 1000 TR USD	36	1000
Total #funds in sample	675	-

Small Efficient Markets		
Benchmark	#Funds in benchmark	#Constituents in benchmark
MSCI Switzerland	69	40
OSE FXLT (Norway)	41	9
MSCI Sweden	39	30
MSCI Italy	33	26
MSCI Denmark	28	20
MSCI Spain	18	25
Total #funds in sample	228	-

World Markets		
Benchmark	#Funds in benchmark	#Constituents in benchmark
MSCI World	121	1649
MSCI World Growth	27	983
MSCI World Value	18	842
MSCI World High Div Yield	6	1649
Total #funds in sample	172	-

Large European Markets		
Benchmark	#Funds in benchmark	#Constituents in benchmark
MSCI EMU	66	240
MSCI Europe Ex UK	15	334
MSCI Europe Mid Cap	12	243
MSCI Europe Value	11	223
MSCI Europe Growth	10	259
MSCI Nordic Countries	10	66
Total #funds in sample	124	-

Large Inefficient Markets		
Benchmark	#Funds in benchmark	#Constituents in benchmark
MSCI EM	55	835
MSCI AC Asia Ex Japan	25	624
MSCI BRIC	17	310
MSCI Ac Asia Pac Ex Jpn	16	704
Total #funds in sample	113	-

Small Inefficient Markets		
Benchmark	#Funds in benchmark	#Constituents in benchmark
MSCI India	43	72
MSCI Russia	28	20
MSCI EM Europe	16	84
MSCI EM Latin America	7	118
MSCI Brazil	5	60
Total #funds in sample	99	-

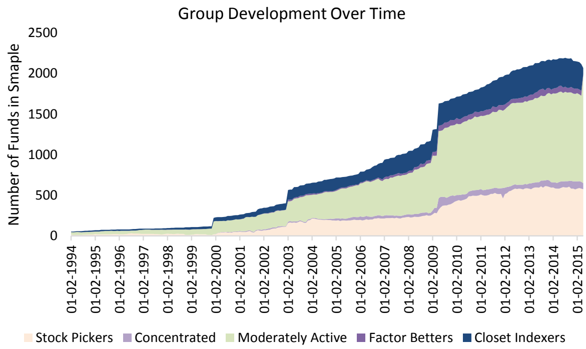
Smallcap Markets		
Benchmark	#Funds in benchmark	#Constituents in benchmark
MSCI Switzerland Small Cap	32	111
MSCI Germany Small Cap	23	110
MSCI Sweden Small Cap	20	90
MSCI Europe Small Cap	10	923
MSCI Japan Small Cap	9	870
Total #funds in sample	94	-

Asia Markets		
Benchmark	#Funds in benchmark	#Constituents in benchmark
MSCI Japan	27	318
MSCI AC Asia Pacific	23	1022
MSCI Hong Kong	7	43
MSCI Korea	5	107
Total #funds in sample	62	-

[a] The subsamples/markets are self-defined based on similar benchmark characteristics.
[b] The name of the benchmark represents the market in which the subsample of funds invest in.

Source: own contribution

Figure A.2: Group development of entire sample



Note: Figure shows the sampled funds sorted into groups between 1994-2015.

Source: own contribution

Table A.2: Numerical example of active share

Fund X ('true active share')			Fund Y (misplaced benchmark and short)			Fund Z (including ADR and cash)			Fund XYZ's benchmark	
Stock	Weight	|Dif|	Stock	Weight	|Dif|	Stock	Weight	|Dif|	Stock	Weight
Maersk B	20.00%	8.36%	Maersk B	40.00%	28.36%	Maersk	20.00%	8.36%	Maersk B	11.64%
Statoil	10.00%	1.75%	Statoil	30.00%	18.26%	Statoil	10.00%	1.75%	Statoil	11.75%
Novo Nordisk B	20.00%	17.80%	Novo Nordisk B	-20.00%	20.00%	Novo Nordisk B (ADR)	20.00%	20.00%	Novo Nordisk B	37.80%
Nordea Bank	10.00%	0.18%	Volvo AB	10.00%	10.00%	Nordea Bank A/S (DK)	10.00%	10.00%	Nordea Bank	10.18%
Carlsberg B	10.00%	10.00%	Novozymes B	10.00%	10.00%	TDC	10.00%	10.00%	Ericsson B	8.51%
Pandora	10.00%	10.00%	Sampo	10.00%	10.00%	Swedish Match	10.00%	10.00%	Danske Bank	7.26%
Investor	10.00%	10.00%	Coloplast	10.00%	10.00%	Vestas Wind Systems	10.00%	10.00%	Svenska Handelsbank A	6.89%
Swedbank	10.00%	10.00%	SEB	10.00%	10.00%	ABB	5.00%	5.00%	Nokia Corp	5.99%
						Cash	5.00%	5.00%		
Sum	100.00%	68.09%		100.00%	116.62%		100.00%	80.11%		100%
Active Share		**34.04%**			**58.31%**			**40.05%**		

Source: own contribution (inspiration from Morningstar methodology paper)

Table A.3: Conversion of portfolios into groups of active management

Active Share relative quintile	Tracking error relative quintile 0-20%	20-40%	40-60%	60-80%	80-100%
80-100%	5	5	5	5	4
60-80%	2	2	2	2	3
40-60%	2	2	2	2	3
20-40%	2	2	2	2	3
0-20%	1	1	1	1	3

Group Label	
5	Stock Pickers
4	Concentrated
3	Factor Betters
2	Moderately Active
1	Closet Indexers

Source: Petajisto (2013) (modified)

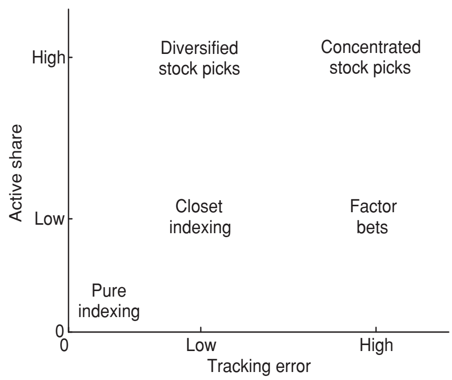
Table A.4: Assigned four-factors for each of the eight markets

The eight markets	Country specific factors
Asia Markets	Japan
World Markets	Global
EU Markets	Europe
Large Inefficient Markets	Global Ex. US
Smallcap Markets	Global
Small Efficient Markets	Europe
Small Inefficient Markets	Global Ex. US
US Markets	North America

Note: All the country specific factors have observations of 256.

Source: Factors from French's data library[31]

Figure A.3: Different types of active management based on active share and tracking error



Source: Cremers and Petajisto (2009)

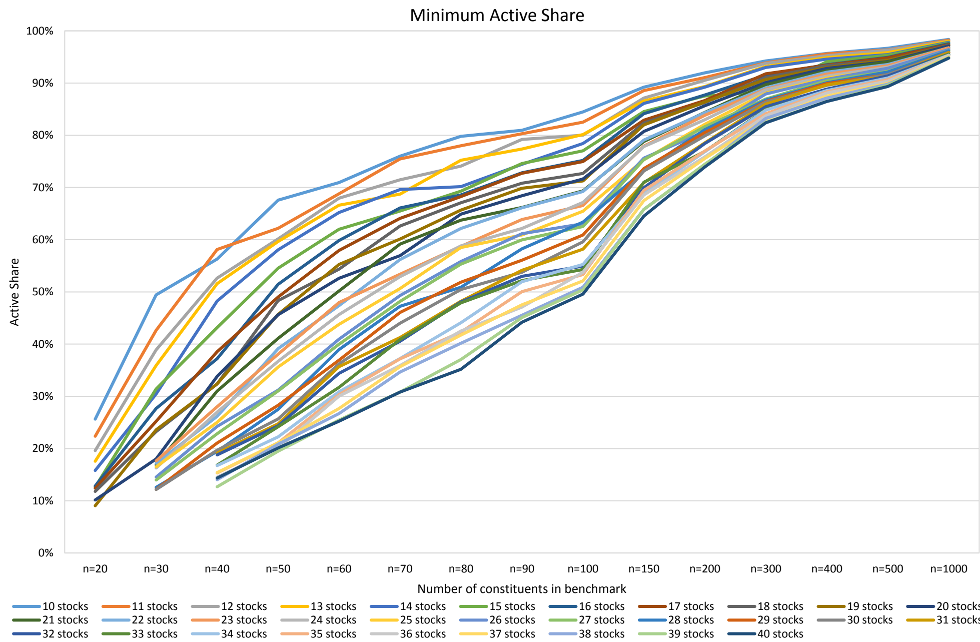
Appendix B

This appendix contain tables and figures related to Chapter 4, Implications of Applying Active Share in Different Markets.

B.1 Monte Carlo Model Graphs and Cut-off Tables

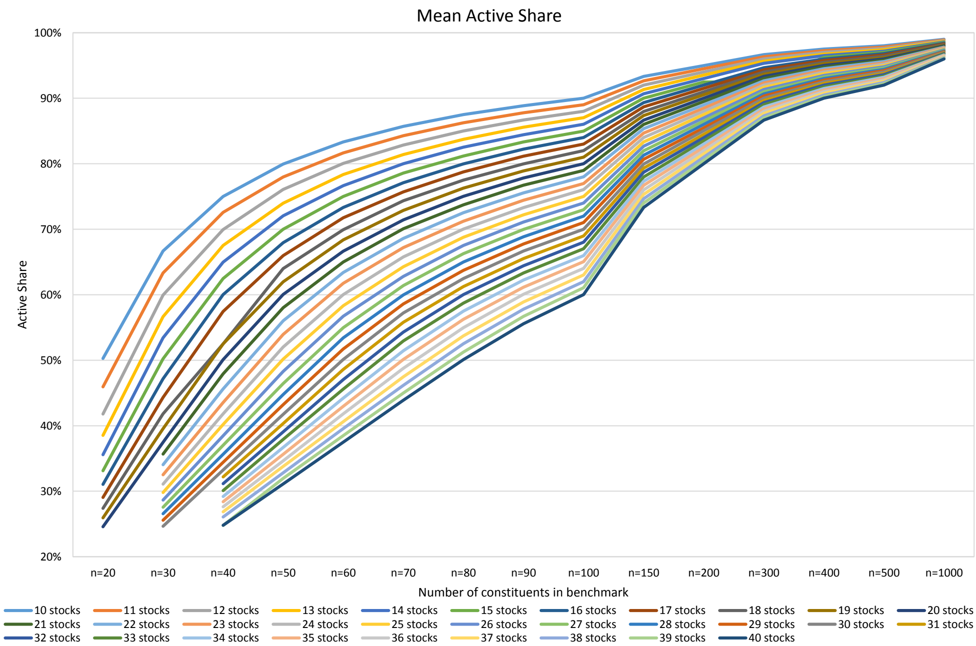
This section illustrates all the performed simulations along with cut-off tables.

Figure B.1: Minimum simulated active share values of 30 funds with different number of stocks



Source: own contribution

Figure B.2: Mean simulated active share values of 30 funds with different number of stocks



Source: own contribution

Table B.1: Simulated cut-off table for funds with 10-30 stocks held

Number of constituents in Benchmark		n=20	n=30	n=40	n=50	n=60	n=70	n=80	n=90	n=100	n=150	n=200	n=300	n=400	n=500	n=1000
10 stocks	Max AS	73.7%	87.2%	90.0%	91.1%	93.3%	94.3%	95.4%	95.2%	96.0%	97.2%	97.9%	98.8%	99.1%	99.4%	99.6%
in fund	Min AS	25.6%	49.4%	56.2%	67.5%	70.9%	76.0%	79.8%	80.9%	84.4%	89.2%	91.9%	94.2%	95.6%	96.6%	98.3%
portfolio	Mean AS	50.2%	66.6%	74.9%	79.9%	83.3%	85.6%	87.5%	88.8%	90.0%	93.3%	94.9%	96.6%	97.4%	98.0%	99.0%
11 stocks	Max AS	72.0%	83.1%	87.0%	92.2%	92.3%	94.9%	93.9%	95.4%	95.8%	96.9%	97.7%	98.5%	98.8%	99.1%	99.5%
in fund	Min AS	22.3%	42.6%	58.1%	62.1%	68.7%	75.4%	77.9%	80.2%	82.5%	88.5%	91.0%	93.8%	95.5%	96.3%	98.2%
portfolio	Mean AS	45.9%	63.3%	72.5%	77.9%	81.6%	84.2%	86.2%	87.7%	89.0%	92.6%	94.5%	96.3%	97.2%	97.8%	98.8%
12 stocks	Max AS	64.7%	81.3%	86.5%	88.0%	92.0%	93.0%	94.2%	94.5%	94.5%	96.8%	97.5%	98.4%	98.8%	99.1%	99.4%
in fund	Min AS	19.6%	38.8%	52.6%	60.1%	67.9%	71.4%	74.1%	79.2%	80.0%	87.1%	90.5%	93.7%	95.2%	96.2%	98.0%
portfolio	Mean AS	41.7%	59.9%	69.9%	76.0%	80.0%	82.8%	85.0%	86.6%	88.0%	92.0%	94.0%	95.9%	97.0%	97.6%	98.8%
13 stocks	Max AS	63.2%	77.5%	85.0%	86.9%	88.9%	90.6%	93.0%	93.6%	93.9%	95.9%	97.1%	97.9%	99.0%	98.9%	99.5%
in fund	Min AS	17.5%	35.9%	51.5%	59.6%	66.6%	68.7%	75.2%	77.3%	80.1%	86.5%	89.3%	93.1%	94.8%	95.8%	98.0%
portfolio	Mean AS	38.5%	56.6%	67.5%	73.9%	78.3%	81.3%	83.7%	85.5%	87.0%	91.3%	93.5%	95.6%	96.7%	97.4%	98.7%
14 stocks	Max AS	60.1%	74.6%	81.7%	87.4%	87.5%	89.2%	92.5%	92.5%	92.8%	95.5%	97.1%	98.2%	98.2%	98.8%	99.3%
in fund	Min AS	15.8%	30.4%	48.2%	58.0%	65.1%	69.6%	70.1%	74.4%	78.4%	86.0%	89.2%	92.9%	94.5%	95.4%	97.8%
portfolio	Mean AS	35.5%	53.4%	64.9%	72.0%	76.6%	80.0%	82.5%	84.4%	86.0%	90.6%	93.0%	95.3%	96.5%	97.1%	98.5%
15 stocks	Max AS	56.4%	71.9%	80.0%	83.8%	88.0%	90.6%	89.9%	92.2%	93.2%	96.0%	96.2%	96.3%	98.2%	98.8%	99.2%
in fund	Min AS	12.6%	31.4%	43.1%	54.5%	62.0%	65.4%	69.2%	74.6%	77.0%	84.5%	87.5%	88.3%	94.0%	95.3%	97.6%
portfolio	Mean AS	33.1%	50.2%	62.4%	70.0%	75.0%	78.5%	81.1%	83.3%	84.9%	90.0%	92.4%	92.4%	96.2%	96.9%	98.4%
16 stocks	Max AS	53.3%	67.1%	78.0%	83.0%	85.4%	89.9%	89.4%	93.4%	91.8%	96.1%	96.5%	97.4%	98.2%	98.6%	99.1%
in fund	Min AS	12.8%	27.6%	37.2%	51.4%	59.8%	66.0%	68.5%	72.8%	75.1%	84.1%	87.7%	91.5%	93.5%	94.9%	97.5%
portfolio	Mean AS	31.0%	47.1%	60.0%	67.9%	73.3%	77.1%	79.9%	82.2%	83.9%	89.3%	92.0%	94.6%	95.9%	96.7%	98.3%
17 stocks	Max AS	51.3%	66.9%	74.3%	79.9%	84.8%	87.3%	88.0%	91.5%	92.9%	94.1%	96.0%	97.0%	98.4%	98.3%	99.1%
in fund	Min AS	12.3%	25.1%	38.5%	49.0%	57.9%	64.0%	68.2%	72.7%	74.9%	82.8%	86.6%	91.7%	93.4%	94.8%	97.3%
portfolio	Mean AS	29.0%	44.3%	57.4%	65.9%	71.7%	75.7%	78.7%	81.1%	82.9%	88.6%	91.5%	94.3%	95.7%	96.6%	98.3%
18 stocks	Max AS	46.4%	61.0%	72.7%	78.2%	83.1%	86.6%	87.2%	89.1%	90.2%	93.4%	95.3%	96.7%	97.7%	98.1%	99.0%
in fund	Min AS	11.7%	23.2%	32.3%	48.3%	54.3%	62.6%	67.0%	70.8%	72.6%	82.3%	86.2%	91.0%	93.3%	94.3%	97.2%
portfolio	Mean AS	27.3%	41.8%	52.5%	64.0%	69.9%	74.3%	77.5%	79.9%	81.9%	87.9%	90.9%	93.9%	95.4%	96.4%	98.1%
19 stocks	Max AS	44.7%	58.8%	72.7%	78.4%	81.1%	84.6%	87.2%	89.0%	89.6%	93.3%	95.2%	96.9%	97.4%	98.0%	99.0%
in fund	Min AS	9.0%	23.5%	32.3%	45.6%	55.2%	60.1%	65.6%	69.8%	71.2%	81.9%	86.3%	90.6%	92.9%	94.3%	97.1%
portfolio	Mean AS	25.9%	39.5%	52.5%	61.9%	68.3%	72.8%	76.2%	78.8%	81.0%	87.3%	90.5%	93.6%	95.2%	96.1%	98.1%
20 stocks	Max AS	43.1%	57.3%	67.3%	75.2%	81.3%	85.1%	86.0%	86.9%	88.5%	93.0%	94.5%	96.7%	97.4%	97.9%	99.0%
in fund	Min AS	10.1%	18.0%	33.8%	45.6%	52.6%	56.9%	64.8%	68.4%	71.6%	80.7%	85.6%	90.0%	92.8%	94.1%	97.1%
portfolio	Mean AS	24.5%	37.4%	50.0%	60.0%	66.6%	71.4%	75.0%	77.8%	80.0%	86.6%	90.0%	93.3%	95.0%	96.0%	97.9%
21 stocks	Max AS	N/A	55.9%	66.5%	74.7%	78.6%	81.4%	85.8%	86.4%	88.0%	91.5%	94.4%	96.1%	97.3%	97.8%	98.8%
in fund	Min AS	N/A	16.8%	30.9%	41.1%	50.1%	59.1%	63.7%	66.1%	69.3%	78.7%	84.3%	89.6%	92.3%	94.0%	96.7%
portfolio	Mean AS	N/A	35.6%	47.9%	58.0%	64.9%	70.0%	73.7%	76.7%	78.9%	86.0%	89.5%	92.9%	94.7%	95.8%	97.9%
22 stocks	Max AS	N/A	52.4%	61.8%	71.4%	76.5%	81.0%	84.7%	85.7%	87.3%	90.7%	94.1%	96.1%	96.7%	97.7%	98.7%
in fund	Min AS	N/A	17.1%	26.1%	39.1%	47.3%	56.1%	62.1%	66.1%	69.2%	79.0%	84.3%	89.0%	92.0%	93.5%	96.7%
portfolio	Mean AS	N/A	34.0%	45.6%	56.0%	63.3%	68.6%	72.5%	75.5%	78.0%	85.3%	88.9%	92.6%	94.4%	95.5%	97.8%
23 stocks	Max AS	N/A	55.7%	63.4%	68.7%	79.6%	80.2%	83.8%	84.7%	87.3%	92.6%	93.2%	95.5%	96.7%	97.5%	98.6%
in fund	Min AS	N/A	17.6%	27.9%	38.0%	47.9%	53.3%	58.7%	63.8%	66.5%	77.9%	83.8%	88.8%	91.7%	93.2%	96.7%
portfolio	Mean AS	N/A	32.5%	43.5%	53.9%	61.7%	67.2%	71.2%	74.4%	76.9%	84.6%	88.4%	92.3%	94.2%	95.3%	97.7%
24 stocks	Max AS	N/A	48.4%	60.3%	67.1%	72.1%	78.3%	80.7%	83.7%	86.3%	90.1%	93.8%	95.2%	96.6%	97.3%	98.6%
in fund	Min AS	N/A	16.2%	26.9%	36.7%	45.6%	52.9%	58.8%	62.1%	67.1%	77.8%	82.9%	88.6%	91.3%	93.0%	96.4%
portfolio	Mean AS	N/A	31.0%	41.8%	52.0%	60.0%	65.7%	70.0%	73.3%	76.0%	84.0%	88.0%	92.0%	94.0%	95.2%	97.5%
25 stocks	Max AS	N/A	47.7%	58.0%	65.2%	72.2%	75.8%	80.2%	83.0%	84.4%	91.0%	93.2%	95.4%	96.2%	97.0%	98.7%
in fund	Min AS	N/A	16.5%	25.0%	35.6%	43.7%	50.6%	58.4%	60.9%	65.4%	75.3%	82.0%	88.0%	90.9%	92.6%	96.1%
portfolio	Mean AS	N/A	29.7%	40.1%	50.1%	58.3%	64.2%	68.7%	72.2%	75.0%	83.3%	87.5%	91.6%	93.7%	94.9%	97.4%
26 stocks	Max AS	N/A	44.4%	57.0%	67.6%	70.4%	75.7%	80.1%	83.7%	83.0%	89.4%	91.9%	94.8%	96.1%	97.2%	98.4%
in fund	Min AS	N/A	14.5%	24.2%	31.1%	40.9%	49.2%	55.8%	61.1%	63.0%	75.6%	80.7%	87.9%	90.7%	92.8%	96.4%
portfolio	Mean AS	N/A	28.6%	38.4%	48.3%	56.7%	62.8%	67.5%	71.1%	74.0%	82.6%	86.9%	91.3%	93.4%	94.8%	97.4%
27 stocks	Max AS	N/A	44.5%	55.0%	61.8%	70.3%	76.6%	79.3%	79.5%	84.7%	89.3%	91.6%	94.4%	95.8%	96.9%	98.4%
in fund	Min AS	N/A	13.9%	22.8%	31.0%	39.9%	48.1%	55.3%	59.9%	62.5%	75.3%	81.6%	86.9%	90.4%	92.2%	96.1%
portfolio	Mean AS	N/A	27.5%	37.0%	46.4%	54.9%	61.4%	66.2%	69.9%	72.9%	81.9%	86.4%	90.9%	93.2%	94.6%	97.3%
28 stocks	Max AS	N/A	46.1%	51.7%	62.6%	68.8%	73.4%	78.0%	79.0%	81.0%	89.5%	90.8%	94.0%	95.7%	96.7%	98.3%
in fund	Min AS	N/A	12.5%	19.4%	27.5%	38.9%	47.2%	50.9%	58.2%	63.3%	73.2%	81.0%	86.7%	90.0%	92.1%	96.1%
portfolio	Mean AS	N/A	26.5%	35.6%	44.7%	53.4%	59.9%	64.9%	68.8%	72.0%	81.3%	86.0%	90.6%	92.9%	94.3%	97.2%
29 stocks	Max AS	N/A	39.7%	52.9%	61.0%	64.7%	71.9%	75.7%	78.8%	81.2%	87.1%	91.1%	94.1%	95.4%	96.3%	98.2%
in fund	Min AS	N/A	12.1%	21.0%	28.2%	36.9%	46.0%	51.8%	56.0%	60.8%	73.6%	80.5%	86.4%	89.9%	91.6%	95.8%
portfolio	Mean AS	N/A	25.5%	34.4%	43.2%	51.7%	58.6%	63.7%	67.7%	71.0%	80.6%	85.4%	90.3%	92.7%	94.2%	97.1%
30 stocks	Max AS	N/A	42.9%	48.0%	56.0%	65.3%	70.7%	75.2%	77.6%	80.0%	87.3%	91.1%	93.7%	95.4%	96.1%	98.0%
in fund	Min AS	N/A	12.1%	19.6%	25.6%	36.2%	44.0%	50.4%	53.7%	59.6%	73.1%	79.9%	86.3%	89.5%	91.6%	95.8%
portfolio	Mean AS	N/A	24.6%	33.2%	41.7%	50.1%	57.2%	62.4%	66.6%	70.0%	79.9%	85.0%	90.0%	92.5%	94.0%	96.9%

This table lists the maximum, minimum and mean simulated active share values from funds holding q=10, q=11, ..., q=30 stocks, and benchmark constituents ranging from n=20, n=30, ..., n=1000.

Source: own contribution

Table B.2: Simulated cut-off table for funds with 31-40, and 100 stocks held

Number of constituents in Benchmark		n=20	n=30	n=40	n=50	n=60	n=70	n=80	n=90	n=100	n=150	n=200	n=300	n=400	n=500	n=1000
31 stocks	Max AS	N/A	N/A	48.3%	57.3%	63.9%	68.9%	73.3%	77.6%	77.9%	86.9%	90.2%	93.7%	95.1%	95.9%	98.0%
in fund	Min AS	N/A	N/A	19.1%	24.7%	35.6%	41.2%	48.2%	54.1%	58.1%	70.9%	78.5%	85.9%	89.6%	91.3%	95.8%
portfolio	Mean AS	N/A	N/A	32.1%	40.3%	48.6%	55.7%	61.2%	65.5%	68.9%	79.3%	84.4%	89.6%	92.2%	93.7%	96.8%
32 stocks	Max AS	N/A	N/A	48.5%	52.4%	60.9%	67.2%	72.3%	76.9%	78.9%	85.8%	90.6%	93.4%	94.9%	96.1%	98.0%
in fund	Min AS	N/A	N/A	18.7%	24.3%	34.4%	40.5%	48.1%	52.9%	54.9%	69.9%	78.4%	85.4%	88.8%	91.3%	95.5%
portfolio	Mean AS	N/A	N/A	31.1%	39.0%	47.0%	54.2%	60.0%	64.4%	68.0%	78.6%	83.9%	89.3%	92.0%	93.5%	96.8%
33 stocks	Max AS	N/A	N/A	45.1%	53.1%	60.4%	66.9%	71.8%	73.5%	76.8%	86.8%	89.2%	92.3%	94.4%	95.7%	97.9%
in fund	Min AS	N/A	N/A	16.8%	24.1%	31.7%	40.8%	47.9%	52.1%	54.2%	71.0%	76.9%	84.9%	88.4%	90.8%	95.5%
portfolio	Mean AS	N/A	N/A	30.0%	37.9%	45.5%	52.9%	58.7%	63.3%	67.0%	77.9%	83.5%	88.9%	91.7%	93.3%	96.7%
34 stocks	Max AS	N/A	N/A	42.5%	50.2%	58.8%	64.5%	69.4%	74.1%	76.1%	86.0%	88.4%	92.4%	94.9%	95.5%	97.9%
in fund	Min AS	N/A	N/A	16.7%	22.2%	30.8%	37.2%	44.1%	51.9%	55.2%	68.8%	76.8%	84.8%	88.5%	90.9%	95.3%
portfolio	Mean AS	N/A	N/A	29.1%	36.6%	44.2%	51.4%	57.5%	62.2%	65.9%	77.3%	83.0%	88.6%	91.4%	93.2%	96.5%
35 stocks	Max AS	N/A	N/A	41.3%	50.3%	59.1%	63.8%	68.5%	71.4%	77.4%	84.8%	88.7%	92.0%	94.3%	95.1%	97.7%
in fund	Min AS	N/A	N/A	15.3%	21.0%	30.3%	37.1%	42.2%	50.0%	53.3%	69.4%	76.9%	84.1%	88.3%	90.6%	95.2%
portfolio	Mean AS	N/A	N/A	28.3%	35.6%	42.9%	50.1%	56.2%	61.1%	65.0%	76.7%	82.5%	88.3%	91.2%	92.9%	96.5%
36 stocks	Max AS	N/A	N/A	41.6%	48.4%	55.5%	62.3%	67.6%	70.3%	73.9%	82.7%	88.3%	92.0%	93.9%	95.1%	97.5%
in fund	Min AS	N/A	N/A	14.5%	20.0%	30.0%	35.9%	42.5%	47.0%	53.7%	68.5%	75.8%	83.7%	88.0%	90.3%	95.2%
portfolio	Mean AS	N/A	N/A	27.6%	34.6%	41.8%	48.7%	54.9%	60.0%	64.0%	75.9%	81.9%	87.9%	91.0%	92.7%	96.4%
37 stocks	Max AS	N/A	N/A	40.2%	47.6%	55.0%	64.7%	66.6%	70.2%	73.9%	83.4%	87.0%	92.1%	93.7%	95.1%	97.5%
in fund	Min AS	N/A	N/A	15.3%	21.1%	27.6%	35.6%	41.7%	47.5%	52.1%	67.4%	75.5%	83.0%	87.5%	89.9%	95.0%
portfolio	Mean AS	N/A	N/A	26.8%	33.7%	40.6%	47.4%	53.7%	58.8%	63.0%	75.3%	81.4%	87.6%	90.7%	92.6%	96.3%
38 stocks	Max AS	N/A	N/A	39.7%	46.8%	55.9%	59.0%	65.3%	69.3%	73.6%	84.0%	87.2%	91.0%	93.2%	94.8%	97.5%
in fund	Min AS	N/A	N/A	14.0%	20.8%	26.6%	34.6%	40.1%	45.5%	50.9%	65.7%	74.3%	83.2%	87.1%	89.7%	94.7%
portfolio	Mean AS	N/A	N/A	26.0%	32.8%	39.5%	46.1%	52.5%	57.8%	61.9%	74.6%	80.9%	87.3%	90.4%	92.3%	96.1%
39 stocks	Max AS	N/A	N/A	38.2%	44.8%	52.4%	58.0%	63.2%	69.1%	74.6%	80.9%	86.5%	91.7%	93.4%	94.6%	97.5%
in fund	Min AS	N/A	N/A	12.6%	19.4%	25.4%	30.7%	37.0%	45.0%	50.3%	65.7%	74.4%	82.4%	86.4%	89.5%	94.8%
portfolio	Mean AS	N/A	N/A	24.7%	31.9%	38.4%	44.9%	51.2%	56.6%	61.0%	73.9%	80.5%	86.9%	90.2%	92.1%	96.0%
40 stocks	Max AS	N/A	N/A	38.1%	44.9%	51.7%	57.0%	62.1%	67.2%	71.2%	80.6%	86.4%	90.9%	93.2%	94.7%	97.3%
in fund	Min AS	N/A	N/A	14.3%	20.1%	25.2%	30.8%	35.1%	44.1%	49.5%	64.5%	73.9%	82.3%	86.4%	89.3%	94.7%
portfolio	Mean AS	N/A	N/A	24.7%	31.1%	37.4%	43.8%	50.1%	55.5%	60.0%	73.3%	80.0%	86.6%	90.0%	91.9%	96.0%
100 stocks	Max AS	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	33.1%	45.3%	57.9%	71.9%	79.5%	83.8%	92.0%
in fund	Min AS	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	17.8%	30.3%	42.0%	61.1%	70.5%	76.0%	88.1%
portfolio	Mean AS	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	24.9%	37.5%	50.1%	66.7%	75.0%	80.0%	90.0%

This table lists the maximum, minimum and mean simulated active share values from funds holding q=31, q=32, ..., q=40, and q=100 stocks, and benchmark constituents ranging from n=20, n=30, ..., n=1000.

Source: own contribution

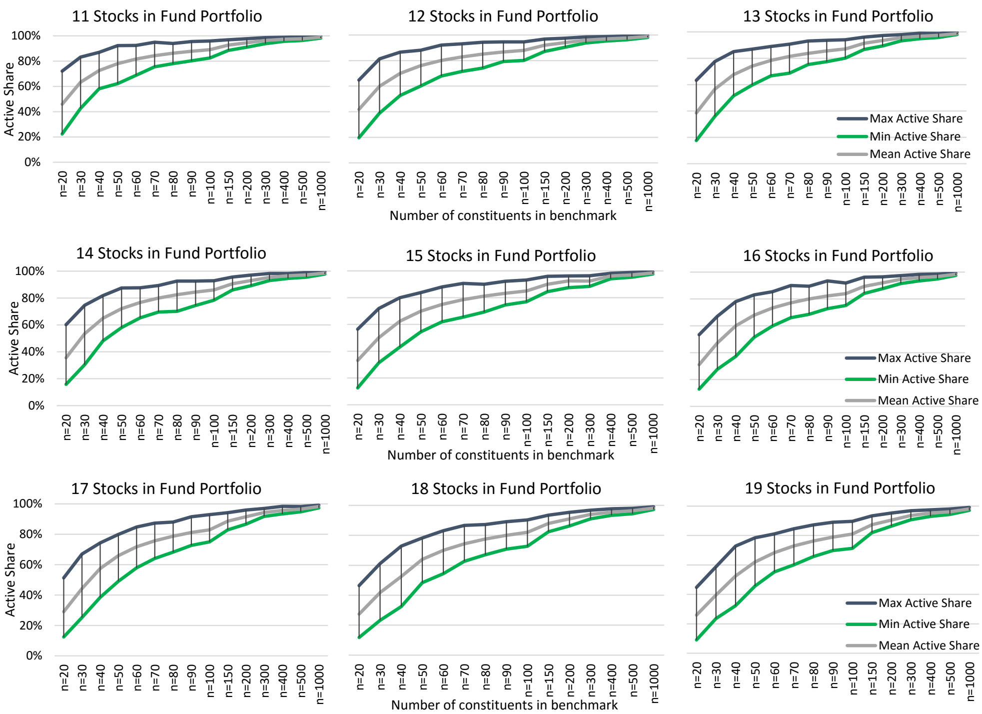
Table B.3: Randomized benchmark weights with fund's actual portfolio weightings

Number of constituents in Benchmark		n=10	n=13	n=16	n=19	n=22	n=25	n=28	n=31	n=40	n=50	n=100	n=150	n=200	n=300	n=400	n=500
TCW	Max AS	76.7%	71.6%	64.0%	59.1%	52.5%	50.4%	42.3%	46.5%	54.4%	62.7%	82.3%	87.9%	91.6%	95.6%	95.7%	96.6%
	Min AS	63.8%	54.2%	43.4%	36.2%	26.5%	19.2%	9.9%	15.4%	23.0%	31.3%	62.8%	74.6%	81.1%	87.1%	89.7%	92.3%
	Mean AS	66.9%	59.2%	51.3%	45.9%	38.3%	32.2%	26.1%	29.0%	37.6%	46.6%	72.1%	81.3%	86.0%	90.7%	93.0%	94.4%
	True AS																**89.8%**
Lannebo Sverige	Max AS	64.0%	51.4%	58.3%	60.1%	67.9%	75.1%	79.0%	79.7%	83.0%	88.1%	93.8%	96.3%	97.1%	98.3%	98.7%	98.9%
	Min AS	23.9%	6.1%	13.6%	18.1%	24.9%	27.8%	33.1%	38.2%	50.9%	58.6%	79.7%	86.3%	89.9%	93.3%	94.9%	95.8%
	Mean AS	38.5%	25.9%	32.3%	38.8%	44.8%	50.0%	54.6%	58.6%	67.6%	74.0%	87.0%	91.3%	93.5%	95.7%	96.8%	97.4%
	True AS		**43.4%**														

[a] As of 05/31/2015 Morningstar Direct reported that TCW and Lannebo Sverige had 28 and 13 number of stocks in their portfolio, respectively.
[b] The 'true active share' is marked with bold.
[c] The red active share values represent outcomes where the fund is investing in stocks outside of the benchmark. These active share values are expected to be higher, since a position outside the benchmark is causing a higher deviation to the portfolio and thus a higher active share.

Source: own contribution

Figure B.3: Simulation of funds with q=11, q=12, ..., q=19 number of stocks held



Source: own contribution

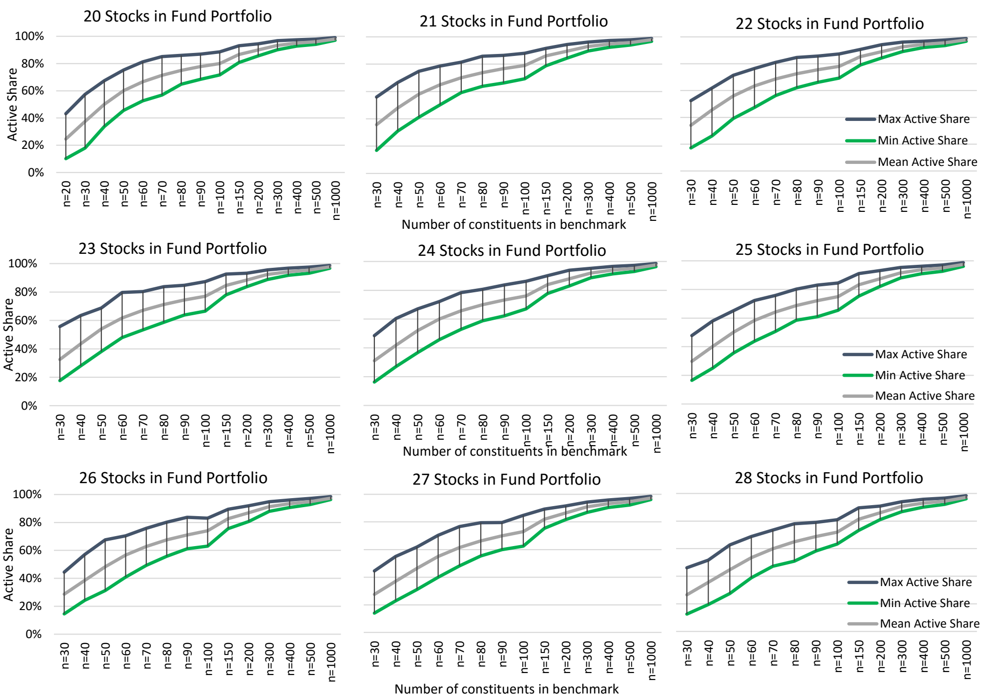
Table B.4: Randomized fund portfolio weights with benchmark's actual portfolio weightings

Number of stocks in fund portfolio		q=10	q=13	q=16	q=19	q=22	q=25	q=28	q=31	q=40	q=50	q=60	q=70	q=80	q=90	q=100
S&P 500	Max AS	98.2%	96.9%	96.7%	96.2%	95.3%	94.2%	93.1%	92.8%	90.9%	89.4%	88.0%	86.7%	85.3%	83.3%	82.5%
	Min AS	97.3%	95.2%	94.8%	94.1%	92.8%	91.1%	90.0%	89.4%	86.6%	84.1%	82.3%	78.7%	77.2%	74.5%	73.7%
	Mean AS	97.3%	95.3%	94.9%	94.3%	93.0%	91.5%	90.5%	90.0%	87.5%	85.4%	84.0%	82.0%	80.7%	78.5%	77.7%
	True AS							**89.8%**								
MSCI Sweden	Max AS	85.0%	77.8%	70.1%	65.2%	64.8%	58.6%	58.6%	57.7%	66.3%	69.2%	71.2%	76.0%	77.7%	80.3%	81.2%
	Min AS	61.0%	40.8%	34.0%	26.9%	24.8%	22.1%	24.4%	24.1%	33.3%	41.1%	48.0%	51.2%	56.2%	60.7%	63.3%
	Mean AS	66.6%	53.2%	49.7%	43.6%	40.6%	38.5%	39.7%	39.5%	47.5%	54.6%	59.7%	63.9%	67.3%	70.1%	72.5%
	True AS		**43.4%**													

[a] S&P 500 and MSCI Sweden have 500 and 30 number of constituents in their benchmarks, respectively[56].
[b] The 'true active share' is marked with bold.
[c] The red active share values represent outcomes where the fund's portfolio has more stocks than the number of constituents in the benchmark. This is causing the active share to be higher.

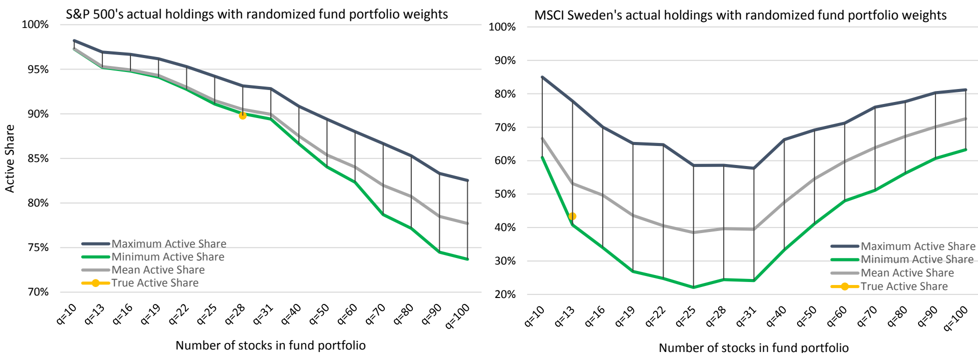
Source: own contribution

Figure B.4: Simulation of funds with q=20, q=21, ..., q=28 number of stocks held



***Source:* own contribution**

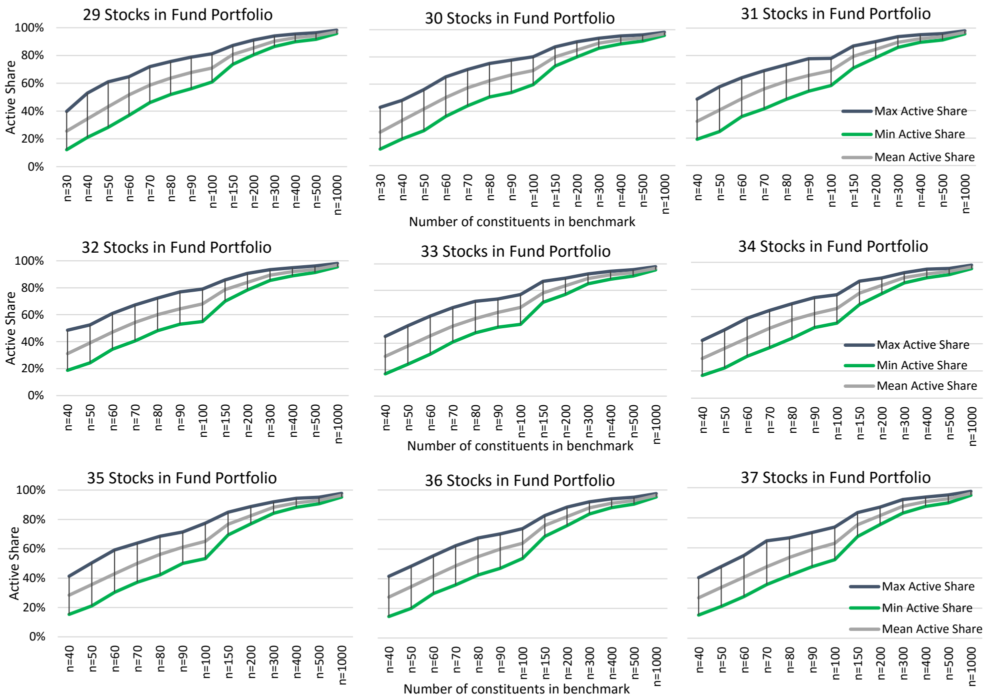
Figure B.5: Simulated active share range for the two benchmarks: S&P 500 and MSCI Sweden



Note: Test of robustness of alternative Monte Carlo Model. Input values are from Table B.4, Appendix B.

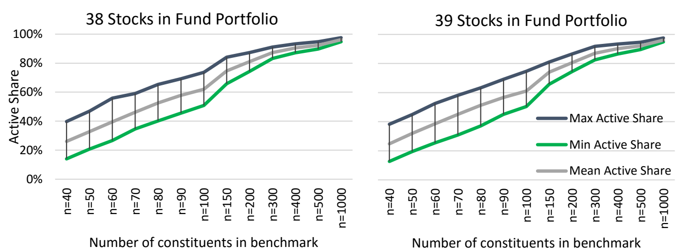
Source: own contribution

Figure B.6: Simulation of funds with q=29, q=30, ..., q=37 number of stocks held



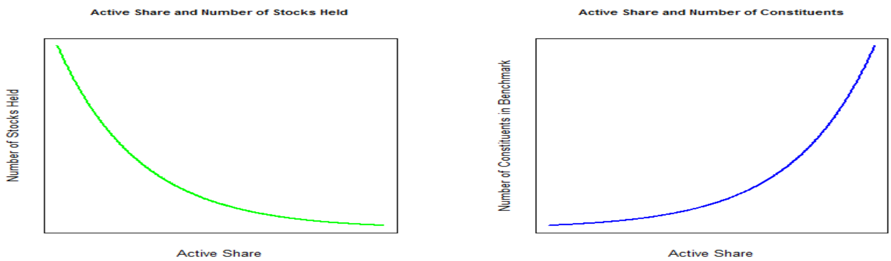
***Source:* own contribution**

Figure B.7: Simulation of funds with q=38 and q=39 number of stocks held



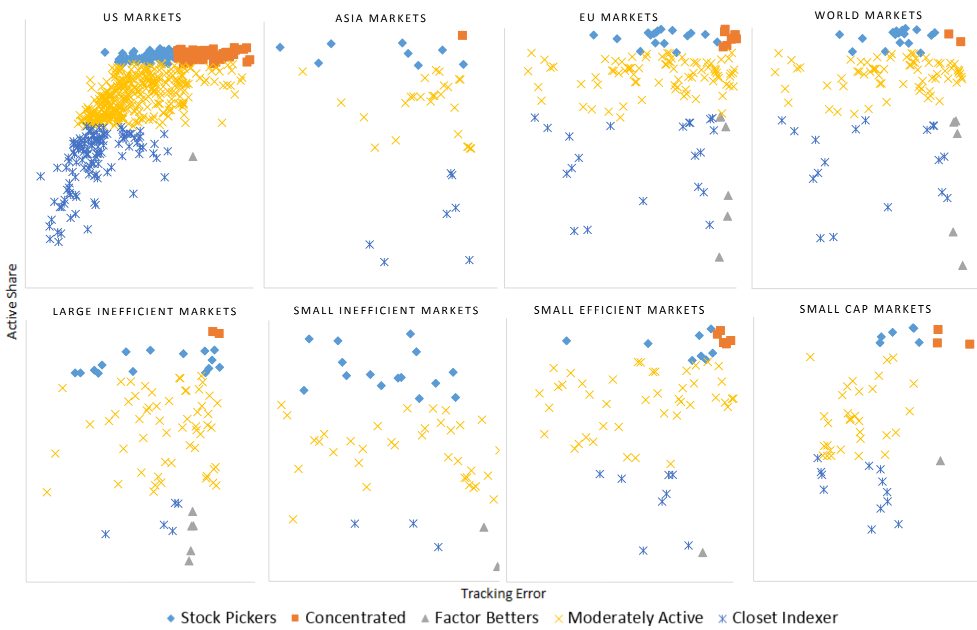
***Source:* own contribution**

Figure B.8: Active share and the effect of a change in number of stocks held, and number of constituents in benchmark



***Source:* own contribution (produced in R)**

Figure B.9: Active share and tracking error combined - total sampled funds



Note: Illustration of Table 6.2. Snapshot of 05/31/2015. For illustration purposes the graphs have been scaled, so the horizontal and vertical axes of each market are relative values.

***Source:* own contribution**

APPENDIX C

Appendix C

This appendix contains all of the conducted performance models for Chapter 7, using Jensen's alpha and Carhart's four-factor model. All performance models have been conducted in the 02/28/1994 - 05/31/2015 period, i.e. corresponding to 256 return observations. However, the return observations vary from model to model depending on accessible data.

C.1 Regression Model Outputs

Table C.1: Performance Model - Jensen's alpha: All sampled funds (gross and net)

	Benchmark Adjusted Returns	
	Gross	Net
MKT	0.494	0.258
	$t = 0.617$	$t = 0.567$
Alpha	-0.061	-0.014
	$t = -1.754^{*}$	$t = -0.697$
Observations	256	256
R^2	0.001	0.001
Adjusted R^2	-0.002	-0.003
Residual Std. Error (df = 254)	0.555	0.315
Note:		*p<0.1; **p<0.05; ***p<0.01
		Estimates are in monthly percentage points

Source: own contribution (produced in R)

Table C.2: Performance Model - Carhart's four-factor model: All sampled funds (gross and net)

	Benchmark Adjusted Returns	
	Gross	Net
MKT	0.130	0.292
	$t = 0.155$	$t = 0.609$
SMB	-3.020	-0.842
	$t = -1.781^{*}$	$t = -0.867$
HML	-1.895	-0.001
	$t = -1.221$	$t = -0.001$
MOM	-0.972	0.159
	$t = -1.065$	$t = 0.305$
Alpha	-0.046	-0.015
	$t = -1.279$	$t = -0.716$
Observations	256	256
R^2	0.022	0.004
Adjusted R^2	0.006	-0.011
Residual Std. Error (df = 251)	0.552	0.316
Note:		*p<0.1; **p<0.05; ***p<0.01
		Estimates are in monthly percentage points

Source: own contribution (produced in R)

Table C.3: Performance Model - Jensen's alpha: All sampled funds (sorted into 5 groups of active management - gross)

	Benchmark Adjusted Gross Returns				
	Closet Indexers	Factor Betters	Moderately Active	Concentrated	Stock Pickers
MKT	0.007	0.041	0.006	0.019	-0.012
	$t = 1.047$	$t = 2.058^{**}$	$t = 0.473$	$t = 0.718$	$t = -0.538$
Alpha	0.001	0.001	0.001	0.004	0.003
	$t = 2.409^{**}$	$t = 1.062$	$t = 1.702^{*}$	$t = 3.537^{***}$	$t = 3.047^{***}$
Observations	253	221	253	185	228
R^2	0.004	0.019	0.001	0.003	0.001
Adjusted R^2	0.0004	0.014	-0.003	-0.003	-0.003
Residual Std. Error	0.004 (df = 251)	0.013 (df = 219)	0.009 (df = 251)	0.017 (df = 183)	0.015 (df = 226)
Note:					*p<0.1; **p<0.05; ***p<0.01
					Estimates are in monthly percentage points

Source: own contribution (produced in R)

Table C.4: Performance Model - Jensen's alpha: All sampled funds (sorted into 5 groups of active management - net)

	Benchmark Adjusted Net Returns				
	Closet Indexers	Factor Betters	Moderately Active	Concentrated	Stock Pickers
MKT	0.007	0.041	0.006	0.019	-0.010
	$t = 1.009$	$t = 2.039^{**}$	$t = 0.453$	$t = 0.723$	$t = -0.482$
Alpha	-0.0004	-0.0002	-0.0002	0.003	0.001
	$t = -1.263$	$t = -0.250$	$t = -0.321$	$t = 2.416^{**}$	$t = 1.580$
Observations	253	221	253	185	253
R^2	0.004	0.019	0.001	0.003	0.001
Adjusted R^2	0.0001	0.014	-0.003	-0.003	-0.003
Residual Std. Error	0.004 (df = 251)	0.013 (df = 219)	0.009 (df = 251)	0.017 (df = 183)	0.015 (df = 251)
Note:					*p<0.1; **p<0.05; ***p<0.01
					Estimates are in monthly percentage points

Source: own contribution (produced in R)

Table C.5: Performance Model - Carhart's four-factor model: All sampled funds (sorted into 5 groups of active management - gross)

	Benchmark Adjusted Gross Returns				
	Closet Indexers	Factor Betters	Moderately Active	Concentrated	Stock Pickers
MKT	0.005	0.035	0.008	0.014	0.003
	$t = 0.697$	$t = 1.650$	$t = 0.562$	$t = 0.477$	$t = 0.132$
SMB	-0.013	-0.055	0.029	0.015	0.075
	$t = -0.915$	$t = -1.238$	$t = 1.036$	$t = 0.243$	$t = 1.635$
HML	-0.029	-0.081	0.010	0.051	0.111
	$t = -2.306^{**}$	$t = -2.074^{**}$	$t = 0.411$	$t = 0.990$	$t = 2.669^{***}$
MOM	0.001	-0.010	0.003	-0.030	0.028
	$t = 0.160$	$t = -0.416$	$t = 0.232$	$t = -0.973$	$t = 1.146$
Alpha	0.001	0.001	0.001	0.004	0.002
	$t = 2.671^{***}$	$t = 1.368$	$t = 1.517$	$t = 3.285^{***}$	$t = 2.278^{**}$
Observations	253	221	253	185	228
R^2	0.029	0.042	0.006	0.016	0.040
Adjusted R^2	0.013	0.024	-0.010	-0.005	0.023
Residual Std. Error	0.004 (df = 248)	0.013 (df = 216)	0.009 (df = 248)	0.017 (df = 180)	0.015 (df = 223)
Note:					*p<0.1; **p<0.05; ***p<0.01
					Estimates are in monthly percentage points

Source: own contribution (produced in R)

Table C.6: Performance Model - Carhart's four-factor model: All sampled funds (sorted into 5 groups of active management - net)

	Benchmark Adjusted Net Returns				
	Closet Indexers	Factor Betters	Moderately Active	Concentrated	Stock Pickers
MKT	0.005	0.034	0.007	0.014	0.005
	$t = 0.689$	$t = 1.640$	$t = 0.551$	$t = 0.485$	$t = 0.220$
SMB	−0.014	−0.056	0.028	0.015	0.082
	$t = -0.995$	$t = -1.264$	$t = 1.019$	$t = 0.235$	$t = 1.839^{*}$
HML	−0.028	−0.081	0.011	0.051	0.110
	$t = -2.252^{**}$	$t = -2.068^{**}$	$t = 0.430$	$t = 0.995$	$t = 2.705^{***}$
MOM	0.002	−0.009	0.004	−0.030	0.029
	$t = 0.248$	$t = -0.389$	$t = 0.254$	$t = -0.968$	$t = 1.197$
Alpha	−0.0003	0.0001	−0.0003	0.003	0.001
	$t = -0.902$	$t = 0.083$	$t = -0.425$	$t = 2.212^{**}$	$t = 0.874$
Observations	253	221	253	185	253
R^2	0.028	0.042	0.006	0.016	0.039
Adjusted R^2	0.013	0.024	-0.010	-0.005	0.024
Residual Std. Error	0.004 (df = 248)	0.013 (df = 216)	0.009 (df = 248)	0.017 (df = 180)	0.014 (df = 248)

Note: *p<0.1; **p<0.05; ***p<0.01
Estimates are in monthly percentage points

Source: own contribution (produced in R)

Table C.7: Performance Model - Jensen's alpha: Closet Index funds (gross)

	Benchmark Adjusted Gross Returns							
	Asia	World	EU	Ineff.	Smallcap	Small Eff.	Small Ineff.	US
MKT	0.013	0.009	0.013	−0.0003	−0.011	−0.0001	0.013	0.007
	$t = 0.651$	$t = 0.732$	$t = 0.651$	$t = -0.041$	$t = -0.728$	$t = -0.011$	$t = 0.651$	$t = 1.029$
Alpha	0.0001	−0.002	0.0001	0.0001	0.002	0.001	0.0001	0.0002
	$t = 0.078$	$t = -2.942^{***}$	$t = 0.078$	$t = 0.176$	$t = 3.433^{***}$	$t = 2.131^{**}$	$t = 0.078$	$t = 0.593$
Observations	146	157	146	148	148	154	146	253
R^2	0.003	0.003	0.003	0.00001	0.004	0.00000	0.003	0.004
Adjusted R^2	-0.004	-0.003	-0.004	-0.007	-0.003	-0.007	-0.004	0.0002
Residual Std. Error	0.010 (df = 144)	0.007 (df = 155)	0.010 (df = 144)	0.005 (df = 146)	0.009 (df = 146)	0.006 (df = 152)	0.010 (df = 144)	0.005 (df = 251)

Note: *p<0.1; **p<0.05; ***p<0.01
Ineff. = Large Inefficient Markets; Small Eff. = Small Efficient Markets; Small Ineff. = Small Inefficient Markets (Estimates are in monthly percentage points)

Source: own contribution (produced in R)

Table C.8: Performance Model - Jensen's alpha: Closet Index funds (net)

	Benchmark Adjusted Net Returns							
	Asia	World	EU	Ineff.	Smallcap	Small Eff.	Small Ineff.	US
MKT	0.013	0.009	0.013	−0.0005	−0.011	0.0001	0.013	0.007
	$t = 0.674$	$t = 0.738$	$t = 0.674$	$t = -0.060$	$t = -0.710$	$t = 0.014$	$t = 0.674$	$t = 1.044$
Alpha	−0.001	−0.0005	−0.001	−0.001	0.001	0.00002	−0.001	−0.001
	$t = -1.472$	$t = -0.791$	$t = -1.472$	$t = -3.659^{***}$	$t = 1.582$	$t = 0.034$	$t = -1.472$	$t = -2.149^{**}$
Observations	146	157	146	148	148	154	146	253
R^2	0.003	0.004	0.003	0.00002	0.003	0.00000	0.003	0.004
Adjusted R^2	-0.004	-0.003	-0.004	-0.007	-0.003	-0.007	-0.004	0.0004
Residual Std. Error	0.010 (df = 144)	0.007 (df = 155)	0.010 (df = 144)	0.005 (df = 146)	0.009 (df = 146)	0.006 (df = 152)	0.010 (df = 144)	0.005 (df = 251)

Note: *p<0.1; **p<0.05; ***p<0.01
Ineff. = Large Inefficient Markets; Small Eff. = Small Efficient Markets; Small Ineff. = Small Inefficient Markets (Estimates are in monthly percentage points)

Source: own contribution (produced in R)

Table C.9: Performance Model - Carhart's four-factor model: Closet Index funds (gross)

	Benchmark Adjusted Gross Returns							
	Asia	World	EU	Ineff.	Smallcap	Small Eff.	Small Ineff.	US
MKT	0.017	0.012	0.017	0.006	−0.009	0.002	0.017	0.007
	$t = 0.850$	$t = 0.855$	$t = 0.850$	$t = 0.701$	$t = -0.538$	$t = 0.149$	$t = 0.850$	$t = 0.988$
SMB	0.043	0.029	0.043	0.050	0.014	0.006	0.043	−0.023
	$t = 1.181$	$t = 0.789$	$t = 1.181$	$t = 2.231^{**}$	$t = 0.299$	$t = 0.228$	$t = 1.181$	$t = -2.244^{**}$
HML	0.042	−0.001	0.042	0.001	0.021	−0.027	0.042	−0.025
	$t = 1.000$	$t = -0.016$	$t = 1.000$	$t = 0.054$	$t = 0.428$	$t = -1.081$	$t = 1.000$	$t = -2.610^{***}$
MOM	0.020	0.010	0.020	0.016	0.017	−0.009	0.020	0.003
	$t = 0.810$	$t = 0.571$	$t = 0.810$	$t = 1.305$	$t = 0.769$	$t = -0.699$	$t = 0.810$	$t = 0.417$
Alpha	−0.0002	−0.002	−0.0002	−0.0001	0.002	0.001	−0.0002	0.0002
	$t = -0.275$	$t = -3.027^{***}$	$t = -0.275$	$t = -0.353$	$t = 3.133^{***}$	$t = 2.255^{**}$	$t = -0.275$	$t = 0.787$
Observations	146	157	146	148	148	154	146	253
R^2	0.027	0.011	0.027	0.051	0.009	0.011	0.027	0.042
Adjusted R^2	-0.001	-0.015	-0.001	0.024	-0.019	-0.015	-0.001	0.026
Residual Std. Error	0.010 (df = 141)	0.007 (df = 152)	0.010 (df = 141)	0.005 (df = 143)	0.009 (df = 143)	0.006 (df = 149)	0.010 (df = 141)	0.005 (df = 248)

Note: *p<0.1; **p<0.05; ***p<0.01
Ineff. = Large Inefficient Markets; Small Eff. = Small Efficient Markets; Small Ineff. = Small Inefficient Markets (Estimates are in monthly percentage points)

Source: own contribution (produced in R)

Table C.10: Performance Model - Carhart's four-factor model: Closet Index funds (net)

	Benchmark Adjusted Net Returns							
	Asia	World	EU	Ineff.	Smallcap	Small Eff.	Small Ineff.	US
MKT	0.017	0.012	0.017	0.006	−0.009	0.002	0.017	0.007
	$t = 0.869$	$t = 0.846$	$t = 0.869$	$t = 0.696$	$t = -0.536$	$t = 0.168$	$t = 0.869$	$t = 1.014$
SMB	0.042	0.032	0.042	0.050	0.016	0.006	0.042	−0.023
	$t = 1.173$	$t = 0.858$	$t = 1.173$	$t = 2.222^{**}$	$t = 0.338$	$t = 0.244$	$t = 1.173$	$t = -2.286^{**}$
HML	0.041	0.002	0.041	0.002	0.022	−0.027	0.041	−0.025
	$t = 0.965$	$t = 0.063$	$t = 0.965$	$t = 0.077$	$t = 0.451$	$t = -1.069$	$t = 0.965$	$t = -2.622^{***}$
MOM	0.020	0.010	0.020	0.017	0.017	−0.009	0.020	0.003
	$t = 0.801$	$t = 0.579$	$t = 0.801$	$t = 1.357$	$t = 0.758$	$t = -0.686$	$t = 0.801$	$t = 0.439$
Alpha	−0.002	−0.001	−0.002	−0.002	0.001	0.0001	−0.002	−0.001
	$t = -1.771^{*}$	$t = -0.967$	$t = -1.771^{*}$	$t = -4.063^{***}$	$t = 1.338$	$t = 0.244$	$t = -1.771^{*}$	$t = -1.944^{*}$
Observations	146	157	146	148	148	154	146	253
R^2	0.027	0.012	0.027	0.051	0.009	0.011	0.027	0.042
Adjusted R^2	-0.001	-0.014	-0.001	0.025	-0.019	-0.015	-0.001	0.027
Residual Std. Error	0.010 (df = 141)	0.007 (df = 152)	0.010 (df = 141)	0.005 (df = 143)	0.009 (df = 143)	0.006 (df = 149)	0.010 (df = 141)	0.005 (df = 248)

Note: *p<0.1; **p<0.05; ***p<0.01
Ineff. = Large Inefficient Markets; Small Eff. = Small Efficient Markets; Small Ineff. = Small Inefficient Markets (Estimates are in monthly percentage points)

Source: own contribution (produced in R)

Table C.11: Performance Model - Jensen's alpha: Factor Betting funds (gross)

	Benchmark Adjusted Gross Returns							
	Asia	World	EU	Ineff.	Smallcap	Small Eff.	Small Ineff.	US
MKT	0.013	0.052	0.022	0.016	−0.092	0.021	0.117	0.024
	$t = 0.336$	$t = 1.943^{*}$	$t = 0.961$	$t = 0.667$	$t = -1.781^{*}$	$t = 0.693$	$t = 3.599^{***}$	$t = 0.965$
Alpha	−0.002	−0.002	−0.001	−0.0001	0.006	0.003	0.003	−0.001
	$t = -0.964$	$t = -1.523$	$t = -0.440$	$t = -0.095$	$t = 2.122^{**}$	$t = 1.691^{*}$	$t = 1.547$	$t = -1.072$
Observations	126	112	123	135	74	129	128	179
R^2	0.001	0.033	0.008	0.003	0.042	0.004	0.093	0.005
Adjusted R^2	-0.007	0.024	-0.001	-0.004	0.029	-0.004	0.086	-0.0004
Residual Std. Error	0.018 (df = 124)	0.014 (df = 110)	0.015 (df = 121)	0.014 (df = 133)	0.023 (df = 72)	0.019 (df = 127)	0.019 (df = 126)	0.015 (df = 177)

Note: *p<0.1; **p<0.05; ***p<0.01
Ineff. = Large Inefficient Markets; Small Eff. = Small Efficient Markets; Small Ineff. = Small Inefficient Markets (Estimates are in monthly percentage points)

Source: own contribution (produced in R)

Table C.12: Performance Model - Jensen's alpha: Factor Betting funds (net)

	Benchmark Adjusted Net Returns							
	Asia	World	EU	Ineff.	Smallcap	Small Eff.	Small Ineff.	US
MKT	0.003	0.052	0.021	0.016	−0.093	0.019	0.116	0.024
	$t = 0.079$	$t = 1.948^{*}$	$t = 0.924$	$t = 0.671$	$t = -1.799^{*}$	$t = 0.641$	$t = 3.580^{***}$	$t = 0.975$
Alpha	−0.003	−0.003	−0.002	−0.002	0.004	0.002	0.001	−0.002
	$t = -1.829^{*}$	$t = -2.485^{**}$	$t = -1.292$	$t = -1.466$	$t = 1.626$	$t = 1.105$	$t = 0.500$	$t = -2.029^{**}$
Observations	126	112	123	135	74	129	128	179
R^2	0.0001	0.033	0.007	0.003	0.043	0.003	0.092	0.005
Adjusted R^2	-0.008	0.025	-0.001	-0.004	0.030	-0.005	0.085	-0.0003
Residual Std. Error	0.019 (df = 124)	0.014 (df = 110)	0.015 (df = 121)	0.014 (df = 133)	0.023 (df = 72)	0.019 (df = 127)	0.019 (df = 126)	0.015 (df = 177)

Note: *p<0.1; **p<0.05; ***p<0.01
Ineff. = Large Inefficient Markets; Small Eff. = Small Efficient Markets; Small Ineff. = Small Inefficient Markets (Estimates are in monthly percentage points)

Source: own contribution (produced in R)

Table C.13: Performance Model - Carhart's four-factor model: Factor Betting funds (gross)

	Benchmark Adjusted Gross Returns							
	Asia	World	EU	Ineff.	Smallcap	Small Eff.	Small Ineff.	US
MKT	0.012	0.065	0.016	0.035	−0.072	0.034	0.128	−0.004
	$t = 0.295$	$t = 2.132^{**}$	$t = 0.549$	$t = 1.288$	$t = -1.299$	$t = 0.959$	$t = 3.601^{***}$	$t = -0.144$
SMB	−0.050	0.020	0.001	0.111	−0.025	−0.102	0.088	0.029
	$t = -0.719$	$t = 0.223$	$t = 0.018$	$t = 1.631$	$t = -0.128$	$t = -1.165$	$t = 0.877$	$t = 0.606$
HML	0.100	−0.118	−0.015	−0.104	0.018	−0.091	−0.107	−0.126
	$t = 1.270$	$t = -1.365$	$t = -0.211$	$t = -1.283$	$t = 0.103$	$t = -1.102$	$t = -0.942$	$t = -3.202^{***}$
MOM	−0.029	−0.005	−0.027	0.013	0.117	0.008	−0.010	−0.032
	$t = -0.621$	$t = -0.121$	$t = -0.769$	$t = 0.334$	$t = 1.214$	$t = 0.174$	$t = -0.189$	$t = -1.247$
Alpha	−0.002	−0.002	−0.0004	−0.0002	0.004	0.003	0.003	−0.001
	$t = -1.079$	$t = -1.451$	$t = -0.271$	$t = -0.165$	$t = 1.527$	$t = 1.799^{*}$	$t = 1.530$	$t = -0.766$
Observations	126	112	123	135	74	129	128	179
R^2	0.031	0.051	0.013	0.044	0.062	0.027	0.110	0.082
Adjusted R^2	-0.001	0.016	-0.021	0.015	0.008	-0.005	0.081	0.061
Residual Std. Error	0.018 (df = 121)	0.014 (df = 107)	0.015 (df = 118)	0.014 (df = 130)	0.023 (df = 69)	0.019 (df = 124)	0.019 (df = 123)	0.014 (df = 174)

Note: *p<0.1; **p<0.05; ***p<0.01
Ineff. = Large Inefficient Markets; Small Eff. = Small Efficient Markets; Small Ineff. = Small Inefficient Markets (Estimates are in monthly percentage points)

Source: own contribution (produced in R)

Table C.14: Performance Model - Carhart's four-factor model: Factor Betting funds (net)

	Benchmark Adjusted Net Returns							
	Asia	World	EU	Ineff.	Smallcap	Small Eff.	Small Ineff.	US
MKT	−0.0004	0.065	0.015	0.035	−0.073	0.033	0.128	−0.003
	$t = -0.009$	$t = 2.122^{**}$	$t = 0.516$	$t = 1.295$	$t = -1.316$	$t = 0.923$	$t = 3.580^{***}$	$t = -0.123$
SMB	−0.065	0.022	0.00000	0.111	−0.023	−0.103	0.087	0.027
	$t = -0.910$	$t = 0.246$	$t = 0.0001$	$t = 1.635$	$t = -0.119$	$t = -1.186$	$t = 0.861$	$t = 0.581$
HML	0.086	−0.116	−0.015	−0.103	0.021	−0.089	−0.109	−0.126
	$t = 1.070$	$t = -1.348$	$t = -0.211$	$t = -1.275$	$t = 0.120$	$t = -1.081$	$t = -0.959$	$t = -3.210^{***}$
MOM	−0.026	−0.005	−0.028	0.013	0.118	0.009	−0.011	−0.032
	$t = -0.553$	$t = -0.138$	$t = -0.778$	$t = 0.345$	$t = 1.226$	$t = 0.203$	$t = -0.203$	$t = -1.237$
Alpha	−0.003	−0.003	−0.002	−0.002	0.003	0.002	0.001	−0.002
	$t = -1.889^{*}$	$t = -2.386^{**}$	$t = -1.091$	$t = -1.486$	$t = 1.065$	$t = 1.239$	$t = 0.545$	$t = -1.736^{*}$
Observations	126	112	123	135	74	129	128	179
R^2	0.029	0.051	0.012	0.044	0.064	0.026	0.109	0.082
Adjusted R^2	-0.003	0.016	-0.021	0.015	0.009	-0.005	0.080	0.061
Residual Std. Error	0.018 (df = 121)	0.014 (df = 107)	0.015 (df = 118)	0.014 (df = 130)	0.023 (df = 69)	0.019 (df = 124)	0.019 (df = 123)	0.014 (df = 174)

Note: *p<0.1; **p<0.05; ***p<0.01
Ineff. = Large Inefficient Markets; Small Eff. = Small Efficient Markets; Small Ineff. = Small Inefficient Markets (Estimates are in monthly percentage points)

Source: own contribution (produced in R)

Table C.15: Performance Model - Jensen's alpha: Moderately Active funds (gross)

	Benchmark Adjusted Gross Returns							
	Asia	World	EU	Ineff.	Smallcap	Small Eff.	Small Ineff.	US
MKT	−0.005	0.016	0.008	−0.005	−0.024	0.017	0.047	0.012
	$t = -0.315$	$t = 1.087$	$t = 0.785$	$t = -0.438$	$t = -1.297$	$t = 1.026$	$t = 2.173^{**}$	$t = 0.889$
Alpha	0.001	0.001	0.001	0.001	0.001	0.003	0.003	0.001
	$t = 1.226$	$t = 1.031$	$t = 1.788^{*}$	$t = 1.734^{*}$	$t = 1.196$	$t = 2.790^{***}$	$t = 2.717^{***}$	$t = 1.552$
Observations	148	148	148	148	148	160	148	253
R^2	0.001	0.008	0.004	0.001	0.011	0.007	0.031	0.003
Adjusted R^2	-0.006	0.001	-0.003	-0.006	0.005	0.0003	0.025	-0.001
Residual Std. Error	0.009 (df = 146)	0.008 (df = 146)	0.007 (df = 146)	0.007 (df = 146)	0.010 (df = 146)	0.011 (df = 158)	0.013 (df = 146)	0.010 (df = 251)

Note: *p<0.1; **p<0.05; ***p<0.01

Ineff. = Large Inefficient Markets; Small Eff. = Small Efficient Markets; Small Ineff. = Small Inefficient Markets (Estimates are in monthly percentage points)

Source: own contribution (produced in R)

Table C.16: Performance Model - Jensen's alpha: Moderately Active funds (net)

	Benchmark Adjusted Net Returns							
	Asia	World	EU	Ineff.	Smallcap	Small Eff.	Small Ineff.	US
MKT	−0.005	0.016	0.008	−0.005	−0.024	0.016	0.047	0.012
	$t = -0.317$	$t = 1.087$	$t = 0.817$	$t = -0.443$	$t = -1.321$	$t = 1.015$	$t = 2.168^{**}$	$t = 0.892$
Alpha	−0.001	−0.001	−0.001	−0.001	−0.0004	0.001	0.001	−0.00002
	$t = -0.684$	$t = -0.829$	$t = -0.923$	$t = -1.122$	$t = -0.486$	$t = 1.320$	$t = 1.085$	$t = -0.026$
Observations	148	148	148	148	148	160	148	253
R^2	0.001	0.008	0.005	0.001	0.012	0.006	0.031	0.003
Adjusted R^2	-0.006	0.001	-0.002	-0.005	0.005	0.0002	0.025	-0.001
Residual Std. Error	0.009 (df = 146)	0.008 (df = 146)	0.007 (df = 146)	0.007 (df = 146)	0.010 (df = 146)	0.011 (df = 158)	0.013 (df = 146)	0.010 (df = 251)

Note: *p<0.1; **p<0.05; ***p<0.01

Ineff. = Large Inefficient Markets; Small Eff. = Small Efficient Markets; Small Ineff. = Small Inefficient Markets (Estimates are in monthly percentage points)

Source: own contribution (produced in R)

Table C.17: Performance Model - Carhart's four-factor model: Moderately Active funds (gross)

	Benchmark Adjusted Gross Returns							
	Asia	World	EU	Ineff.	Smallcap	Small Eff.	Small Ineff.	US
MKT	−0.004	0.013	0.012	0.006	−0.012	0.017	0.049	0.012
	$t = -0.209$	$t = 0.762$	$t = 0.982$	$t = 0.506$	$t = -0.630$	$t = 0.824$	$t = 2.069^{**}$	$t = 0.801$
SMB	0.022	0.044	0.017	0.028	−0.119	−0.007	0.104	0.001
	$t = 0.686$	$t = 0.993$	$t = 0.565$	$t = 0.901$	$t = -2.231^{**}$	$t = -0.141$	$t = 1.667^{*}$	$t = 0.038$
HML	0.002	−0.059	−0.022	0.005	0.022	0.022	0.052	−0.002
	$t = 0.048$	$t = -1.287$	$t = -0.705$	$t = 0.138$	$t = 0.394$	$t = 0.452$	$t = 0.709$	$t = -0.108$
MOM	0.029	−0.028	−0.001	0.039	0.031	0.012	0.002	0.002
	$t = 1.324$	$t = -1.353$	$t = -0.065$	$t = 2.267^{**}$	$t = 1.230$	$t = 0.495$	$t = 0.045$	$t = 0.115$
Alpha	0.001	0.001	0.001	0.001	0.001	0.002	0.003	0.001
	$t = 1.047$	$t = 1.259$	$t = 1.668^{*}$	$t = 1.008$	$t = 1.118$	$t = 2.461^{**}$	$t = 2.320^{**}$	$t = 1.511$
Observations	148	148	148	148	148	160	148	253
R^2	0.022	0.035	0.010	0.045	0.053	0.009	0.051	0.003
Adjusted R^2	-0.005	0.008	-0.018	0.018	0.026	-0.016	0.025	-0.013
Residual Std. Error	0.009 (df = 143)	0.008 (df = 143)	0.007 (df = 143)	0.007 (df = 143)	0.010 (df = 143)	0.012 (df = 155)	0.013 (df = 143)	0.010 (df = 248)

Note: *p<0.1; **p<0.05; ***p<0.01

Ineff. = Large Inefficient Markets; Small Eff. = Small Efficient Markets; Small Ineff. = Small Inefficient Markets (Estimates are in monthly percentage points)

Source: own contribution (produced in R)

Table C.18: Performance Model - Carhart's four-factor model: Moderately Active funds (net)

	Benchmark Adjusted Net Returns							
	Asia	World	EU	Ineff.	Smallcap	Small Eff.	Small Ineff.	US
MKT	-0.004	0.013	0.013	0.006	-0.013	0.017	0.049	0.012
	$t = -0.215$	$t = 0.763$	$t = 1.007$	$t = 0.499$	$t = -0.640$	$t = 0.814$	$t = 2.066^{**}$	$t = 0.811$
SMB	0.021	0.045	0.018	0.028	-0.120	-0.007	0.104	0.001
	$t = 0.670$	$t = 1.003$	$t = 0.594$	$t = 0.889$	$t = -2.249^{**}$	$t = -0.154$	$t = 1.679^{*}$	$t = 0.027$
HML	0.001	-0.058	-0.022	0.005	0.022	0.023	0.052	-0.002
	$t = 0.020$	$t = -1.269$	$t = -0.697$	$t = 0.133$	$t = 0.405$	$t = 0.468$	$t = 0.715$	$t = -0.099$
MOM	0.029	-0.028	-0.001	0.039	0.032	0.013	0.002	0.002
	$t = 1.321$	$t = -1.330$	$t = -0.057$	$t = 2.263^{**}$	$t = 1.269$	$t = 0.511$	$t = 0.049$	$t = 0.126$
Alpha	-0.001	-0.0004	-0.001	-0.001	-0.0005	0.001	0.001	-0.00002
	$t = -0.797$	$t = -0.569$	$t = -0.925$	$t = -1.731^{*}$	$t = -0.549$	$t = 1.072$	$t = 0.769$	$t = -0.032$
Observations	148	148	148	148	148	160	148	253
R^2	0.022	0.034	0.010	0.045	0.054	0.009	0.051	0.003
Adjusted R^2	-0.006	0.007	-0.017	0.018	0.028	-0.016	0.025	-0.013
Residual Std. Error	0.009 (df = 143)	0.008 (df = 143)	0.007 (df = 143)	0.007 (df = 143)	0.010 (df = 143)	0.012 (df = 155)	0.013 (df = 143)	0.010 (df = 248)

Note: *p<0.1; **p<0.05; ***p<0.01
Ineff. = Large Inefficient Markets; Small Eff. = Small Efficient Markets; Small Ineff. = Small Inefficient Markets (Estimates are in monthly percentage points)

Source: own contribution (produced in R)

Table C.19: Performance Model - Jensen's alpha: Concentraded funds (gross)

	Benchmark Adjusted Gross Returns							
	Asia	World	EU	Ineff.	Smallcap	Small Eff.	Small Ineff.	US
MKT	-0.063	0.082	0.062	0.014	-0.121	-0.004	0.179	0.057
	$t = -1.109$	$t = 1.616$	$t = 2.327^{**}$	$t = 0.300$	$t = -2.037^{**}$	$t = -0.158$	$t = 3.543^{***}$	$t = 1.448$
Alpha	0.003	0.005	0.001	0.002	0.0004	0.003	0.004	0.002
	$t = 1.294$	$t = 1.948^{*}$	$t = 0.889$	$t = 1.012$	$t = 0.129$	$t = 2.253^{**}$	$t = 1.566$	$t = 0.882$
Observations	94	138	125	111	122	148	103	253
R^2	0.013	0.019	0.042	0.001	0.033	0.0002	0.111	0.008
Adjusted R^2	0.002	0.012	0.034	-0.008	0.025	-0.007	0.102	0.004
Residual Std. Error	0.023 (df = 92)	0.027 (df = 136)	0.017 (df = 123)	0.023 (df = 109)	0.031 (df = 120)	0.016 (df = 146)	0.028 (df = 101)	0.028 (df = 251)

Note: *p<0.1; **p<0.05; ***p<0.01
Ineff. = Large Inefficient Markets; Small Eff. = Small Efficient Markets; Small Ineff. = Small Inefficient Markets (Estimates are in monthly percentage points)

Source: own contribution (produced in R)

Table C.20: Performance Model - Jensen's alpha: Concentraded funds (net)

	Benchmark Adjusted Net Returns							
	Asia	World	EU	Ineff.	Smallcap	Small Eff.	Small Ineff.	US
MKT	-0.065	0.081	0.061	0.013	-0.120	-0.004	0.179	0.057
	$t = -1.152$	$t = 1.587$	$t = 2.317^{**}$	$t = 0.294$	$t = -2.030^{**}$	$t = -0.152$	$t = 3.553^{***}$	$t = 1.447$
Alpha	0.003	0.003	-0.0004	0.0005	-0.001	0.001	0.002	0.0004
	$t = 1.074$	$t = 1.123$	$t = -0.258$	$t = 0.206$	$t = -0.534$	$t = 1.073$	$t = 0.791$	$t = 0.207$
Observations	94	138	125	111	122	148	103	253
R^2	0.014	0.018	0.042	0.001	0.033	0.0002	0.111	0.008
Adjusted R^2	0.004	0.011	0.034	-0.008	0.025	-0.007	0.102	0.004
Residual Std. Error	0.023 (df = 92)	0.027 (df = 136)	0.017 (df = 123)	0.023 (df = 109)	0.031 (df = 120)	0.016 (df = 146)	0.028 (df = 101)	0.028 (df = 251)

Note: *p<0.1; **p<0.05; ***p<0.01
Ineff. = Large Inefficient Markets; Small Eff. = Small Efficient Markets; Small Ineff. = Small Inefficient Markets (Estimates are in monthly percentage points)

Source: own contribution (produced in R)

Table C.21: Performance Model - Carhart's four-factor model: Concentraded funds (gross)

	Benchmark Adjusted Gross Returns							
	Asia	World	EU	Ineff.	Smallcap	Small Eff.	Small Ineff.	US
MKT	−0.070	0.045	0.072	0.053	−0.090	0.025	0.197	0.058
	$t = -1.193$	$t = 0.811$	$t = 2.118^{**}$	$t = 1.013$	$t = -1.384$	$t = 0.810$	$t = 3.510^{***}$	$t = 1.368$
SMB	0.036	0.228	0.016	0.058	−0.378	0.037	0.347	−0.047
	$t = 0.324$	$t = 1.465$	$t = 0.192$	$t = 0.451$	$t = -2.019^{**}$	$t = 0.512$	$t = 2.113^{**}$	$t = -0.769$
HML	0.023	0.068	−0.030	−0.207	−0.086	−0.093	0.124	−0.053
	$t = 0.195$	$t = 0.436$	$t = -0.350$	$t = -1.368$	$t = -0.452$	$t = -1.210$	$t = 0.688$	$t = -0.919$
MOM	−0.073	−0.085	0.010	0.019	0.038	0.028	0.026	0.012
	$t = -1.118$	$t = -1.200$	$t = 0.239$	$t = 0.281$	$t = 0.444$	$t = 0.737$	$t = 0.308$	$t = 0.336$
Alpha	0.003	0.005	0.001	0.002	0.0001	0.003	0.004	0.002
	$t = 1.308$	$t = 1.950^{*}$	$t = 0.761$	$t = 0.850$	$t = 0.025$	$t = 1.919^{*}$	$t = 1.460$	$t = 0.907$
Observations	94	138	125	111	122	148	103	253
R^2	0.027	0.045	0.044	0.026	0.068	0.019	0.150	0.013
Adjusted R^2	-0.016	0.016	0.012	-0.011	0.036	-0.009	0.115	-0.002
Residual Std. Error	0.023 (df = 89)	0.027 (df = 133)	0.018 (df = 120)	0.023 (df = 106)	0.030 (df = 117)	0.016 (df = 143)	0.028 (df = 98)	0.028 (df = 248)

Note: *p<0.1; **p<0.05; ***p<0.01
Ineff. = Large Inefficient Markets; Small Eff. = Small Efficient Markets; Small Ineff. = Small Inefficient Markets (Estimates are in monthly percentage points)

Source: own contribution (produced in R)

Table C.22: Performance Model - Carhart's four-factor model: Concentraded funds (net)

	Benchmark Adjusted Net Returns							
	Asia	World	EU	Ineff.	Smallcap	Small Eff.	Small Ineff.	US
MKT	−0.072	0.043	0.072	0.052	−0.090	0.025	0.197	0.058
	$t = -1.227$	$t = 0.774$	$t = 2.122^{**}$	$t = 0.995$	$t = -1.386$	$t = 0.812$	$t = 3.518^{***}$	$t = 1.366$
SMB	0.051	0.224	0.015	0.059	−0.376	0.038	0.344	−0.047
	$t = 0.460$	$t = 1.446$	$t = 0.178$	$t = 0.456$	$t = -2.014^{**}$	$t = 0.519$	$t = 2.108^{**}$	$t = -0.761$
HML	0.029	0.069	−0.034	−0.206	−0.085	−0.092	0.122	−0.053
	$t = 0.242$	$t = 0.446$	$t = -0.398$	$t = -1.361$	$t = -0.444$	$t = -1.202$	$t = 0.679$	$t = -0.910$
MOM	−0.078	−0.086	0.009	0.016	0.037	0.028	0.025	0.012
	$t = -1.192$	$t = -1.229$	$t = 0.206$	$t = 0.243$	$t = 0.430$	$t = 0.741$	$t = 0.300$	$t = 0.333$
Alpha	0.003	0.003	−0.001	0.0002	−0.002	0.001	0.002	0.0004
	$t = 1.086$	$t = 1.155$	$t = -0.329$	$t = 0.085$	$t = -0.631$	$t = 0.782$	$t = 0.700$	$t = 0.246$
Observations	94	138	125	111	122	148	103	253
R^2	0.031	0.045	0.044	0.025	0.067	0.019	0.150	0.013
Adjusted R^2	-0.013	0.016	0.012	-0.011	0.035	-0.009	0.115	-0.003
Residual Std. Error	0.023 (df = 89)	0.027 (df = 133)	0.018 (df = 120)	0.023 (df = 106)	0.030 (df = 117)	0.016 (df = 143)	0.028 (df = 98)	0.028 (df = 248)

Note: *p<0.1; **p<0.05; ***p<0.01
Ineff. = Large Inefficient Markets; Small Eff. = Small Efficient Markets; Small Ineff. = Small Inefficient Markets (Estimates are in monthly percentage points)

Source: own contribution (produced in R)

Table C.23: Performance Model - Jensen's alpha: Stock Picking funds (gross)

	Benchmark Adjusted Gross Returns							
	Asia	World	EU	Ineff.	Smallcap	Small Eff.	Small Ineff.	US
MKT	0.007	0.011	0.003	−0.027	−0.050	0.003	−0.004	−0.003
	$t = 0.297$	$t = 0.426$	$t = 0.136$	$t = -1.247$	$t = -1.961^{*}$	$t = 0.163$	$t = -0.123$	$t = -0.099$
Alpha	0.001	0.003	0.004	0.002	0.002	0.003	0.004	0.003
	$t = 1.061$	$t = 2.648^{***}$	$t = 3.506^{***}$	$t = 1.618$	$t = 1.941^{*}$	$t = 2.363^{**}$	$t = 2.257^{**}$	$t = 2.147^{**}$
Observations	148	194	157	154	148	148	146	253
R^2	0.001	0.001	0.0001	0.010	0.026	0.0002	0.0001	0.00004
Adjusted R^2	-0.006	-0.004	-0.006	0.004	0.019	-0.007	-0.007	-0.004
Residual Std. Error	0.013 (df = 146)	0.016 (df = 192)	0.016 (df = 155)	0.013 (df = 152)	0.014 (df = 146)	0.014 (df = 146)	0.019 (df = 144)	0.019 (df = 251)

Note: *p<0.1; **p<0.05; ***p<0.01
Ineff. = Large Inefficient Markets; Small Eff. = Small Efficient Markets; Small Ineff. = Small Inefficient Markets (Estimates are in monthly percentage points)

Source: own contribution (produced in R)

Table C.24: Performance Model - Jensen's alpha: Stock Picking funds (net)

	Benchmark Adjusted Net Returns							
	Asia	World	EU	Ineff.	Smallcap	Small Eff.	Small Ineff.	US
MKT	0.006	0.009	0.003	−0.026	−0.050	0.003	−0.004	−0.003
	$t = 0.257$	$t = 0.374$	$t = 0.122$	$t = -1.219$	$t = -1.976^{*}$	$t = 0.124$	$t = -0.133$	$t = -0.095$
Alpha	−0.0004	0.002	0.002	−0.00002	0.001	0.001	0.002	0.002
	$t = -0.352$	$t = 1.410$	$t = 1.912^{*}$	$t = -0.017$	$t = 0.552$	$t = 0.987$	$t = 1.120$	$t = 1.291$
Observations	148	194	157	154	148	148	146	253
R^2	0.0005	0.001	0.0001	0.010	0.026	0.0001	0.0001	0.00004
Adjusted R^2	-0.006	-0.004	-0.006	0.003	0.019	-0.007	-0.007	-0.004
Residual Std. Error	0.013 (df = 146)	0.016 (df = 192)	0.016 (df = 155)	0.013 (df = 152)	0.014 (df = 146)	0.014 (df = 146)	0.019 (df = 144)	0.019 (df = 251)

Note: *p<0.1; **p<0.05; ***p<0.01
Ineff. = Large Inefficient Markets; Small Eff. = Small Efficient Markets; Small Ineff. = Small Inefficient Markets (Estimates are in monthly percentage points)

Source: own contribution (produced in R)

Table C.25: Performance Model - Carhart's four-factor model: Stock Picking funds (gross)

	Benchmark Adjusted Gross Returns							
	Asia	World	EU	Ineff.	Smallcap	Small Eff.	Small Ineff.	US
MKT	0.009	0.016	0.006	−0.016	−0.036	−0.008	−0.002	0.010
	$t = 0.365$	$t = 0.602$	$t = 0.207$	$t = -0.667$	$t = -1.271$	$t = -0.299$	$t = -0.058$	$t = 0.336$
SMB	0.034	0.044	0.022	0.011	−0.094	0.061	0.053	0.013
	$t = 0.778$	$t = 0.759$	$t = 0.333$	$t = 0.183$	$t = -1.247$	$t = 0.966$	$t = 0.596$	$t = 0.298$
HML	0.027	0.078	−0.012	0.053	−0.058	0.022	0.125	0.078
	$t = 0.536$	$t = 1.661^{*}$	$t = -0.179$	$t = 0.736$	$t = -0.750$	$t = 0.332$	$t = 1.185$	$t = 1.935^{*}$
MOM	−0.018	0.002	−0.0005	0.047	0.017	−0.022	0.032	0.008
	$t = -0.609$	$t = 0.080$	$t = -0.014$	$t = 1.367$	$t = 0.480$	$t = -0.683$	$t = 0.645$	$t = 0.319$
Alpha	0.001	0.003	0.004	0.001	0.002	0.003	0.003	0.002
	$t = 0.858$	$t = 2.162^{**}$	$t = 3.303^{***}$	$t = 1.031$	$t = 1.959^{*}$	$t = 2.353^{**}$	$t = 1.762^{*}$	$t = 1.867^{*}$
Observations	148	194	157	154	148	148	146	253
R^2	0.007	0.017	0.001	0.025	0.041	0.011	0.013	0.015
Adjusted R^2	-0.021	-0.004	-0.025	-0.001	0.014	-0.016	-0.015	-0.001
Residual Std. Error	0.013 (df = 143)	0.016 (df = 189)	0.016 (df = 152)	0.013 (df = 149)	0.014 (df = 143)	0.014 (df = 143)	0.019 (df = 141)	0.019 (df = 248)

Note: *p<0.1; **p<0.05; ***p<0.01
Ineff. = Large Inefficient Markets; Small Eff. = Small Efficient Markets; Small Ineff. = Small Inefficient Markets (Estimates are in monthly percentage points)

Source: own contribution (produced in R)

Table C.26: Performance Model - Carhart's four-factor model: Stock Picking funds (net)

	Benchmark Adjusted Net Returns							
	Asia	World	EU	Ineff.	Smallcap	Small Eff.	Small Ineff.	US
MKT	0.007	0.015	0.006	−0.015	−0.036	−0.009	−0.002	0.010
	$t = 0.301$	$t = 0.559$	$t = 0.200$	$t = -0.641$	$t = -1.294$	$t = -0.332$	$t = -0.064$	$t = 0.339$
SMB	0.026	0.045	0.020	0.012	−0.093	0.059	0.052	0.013
	$t = 0.588$	$t = 0.774$	$t = 0.310$	$t = 0.199$	$t = -1.238$	$t = 0.941$	$t = 0.579$	$t = 0.294$
HML	0.028	0.079	−0.010	0.052	−0.054	0.022	0.125	0.077
	$t = 0.539$	$t = 1.685^{*}$	$t = -0.155$	$t = 0.727$	$t = -0.701$	$t = 0.331$	$t = 1.185$	$t = 1.931^{*}$
MOM	−0.027	0.003	0.001	0.047	0.017	−0.023	0.033	0.008
	$t = -0.908$	$t = 0.091$	$t = 0.023$	$t = 1.359$	$t = 0.494$	$t = -0.689$	$t = 0.659$	$t = 0.321$
Alpha	−0.001	0.001	0.002	−0.001	0.001	0.001	0.001	0.001
	$t = -0.475$	$t = 0.965$	$t = 1.785^{*}$	$t = -0.506$	$t = 0.599$	$t = 1.039$	$t = 0.685$	$t = 1.025$
Observations	148	194	157	154	148	148	146	253
R^2	0.008	0.017	0.001	0.025	0.041	0.011	0.013	0.015
Adjusted R^2	-0.020	-0.004	-0.025	-0.002	0.014	-0.017	-0.015	-0.001
Residual Std. Error	0.013 (df = 143)	0.016 (df = 189)	0.016 (df = 152)	0.013 (df = 149)	0.014 (df = 143)	0.014 (df = 143)	0.019 (df = 141)	0.019 (df = 248)

Note: *p<0.1; **p<0.05; ***p<0.01
Ineff. = Large Inefficient Markets; Small Eff. = Small Efficient Markets; Small Ineff. = Small Inefficient Markets (Estimates are in monthly percentage points)

Source: own contribution (produced in R)

APPENDIX D

Appendix D

This appendix contains the regression model assumptions for the performance evaluation as referred to in Chapter 3, and performed in Chapter 7.

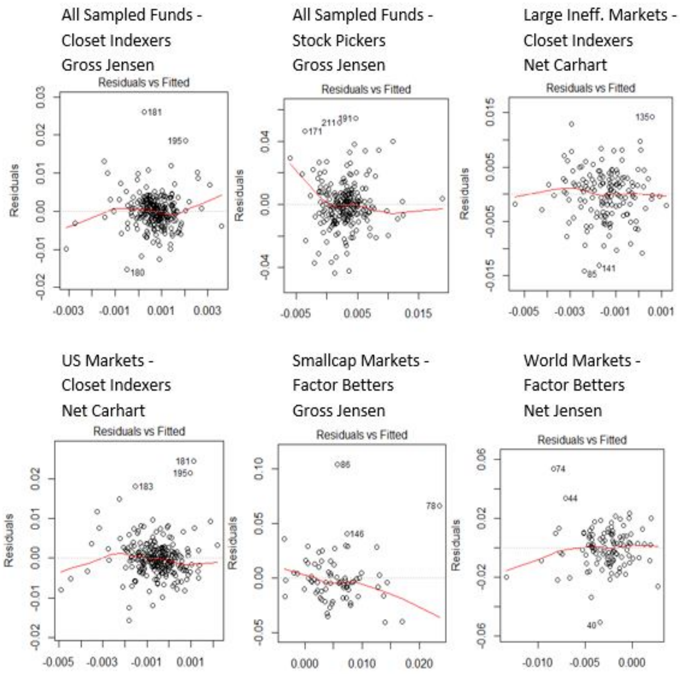
D.1 Testing for Linearity and Homoscedasticity

To test if the linearity assumption and the homoscedasticity (constant variance assumption) are satisfied, a number of residual plots have been made in R. The plots are found in Figure D.4, D.5, and D.6, which illustrate the predicted returns (horizontal axis) against the residuals (vertical axis). In order for the linearity assumption to be met, there should be no pattern amongst the residuals[33]. While looking at the plots, it appears that very few are violating this assumption. The two models, 'Smallcap Markets - Factor Betters Gross Jensen' and 'US Markets - Factor Betters Net Carhart' are particularly not seen as fulfilling the linearity assumption. However, the remaining models are viewed as having a sufficient linearity.
For the constant variance assumption, the same plots in Figure D.4, D.5, and D.6 are used. In order for the constant variance assumption to be fulfilled, there should be no trend in the residuals, i.e. no increasing or decreasing residual variance. A way to determine if the constant variance assumption is violated is to observe if the residuals are 'fanning out' (ibid.). The 15 performance models show no sign of an increasing nor do they demonstrate decreasing variance, and thus, the constant variance assumption is met.

D.2 Testing for Normality

To test the normality assumption the residuals have been graphed on quintile-quantile (Q-Q) plots, using R. The Q-Q plots are illustrated in Figure D.4, D.5, and D.6 for the 15 performance models. The residuals have been arranged from smallest to largest. In order for the linearity assumption to be satisfied, the residuals have to fall roughly on the 45 degree line[33]. Figure D.4, D.5, and D.6 shows that most of the models lie around the 45 degree line.

Figure D.1: Testing for linearity and homoscedasticity



Source: own contribution (computed in R)

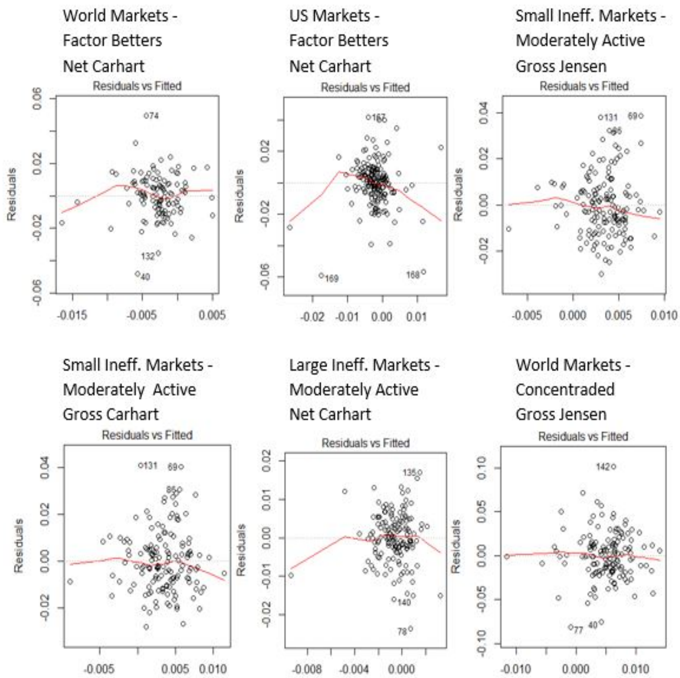
D.3 Testing for Multicollinearity and Autocorrelation

The multicollinearity assumption requires that independence amongst the independent variables is apparent. In this thesis, tests of multicollinearity have been carried out in R using the variance inflation factor[1] (denoted VIF). A VIF value above 10 signals that the model has a collinearity problem[33]. The VIF values for the regression models are illustrated in Table D.1. From observing the table it appears that none of the performance models have a VIF>10, and therefore, the models do not have an issue with dependence amongst the independent variables.

To test whether the residuals are autocorrelated, i.e. independence among residuals, the Durbin-Watson statistic (denoted D-W stat) has been applied. With a significance

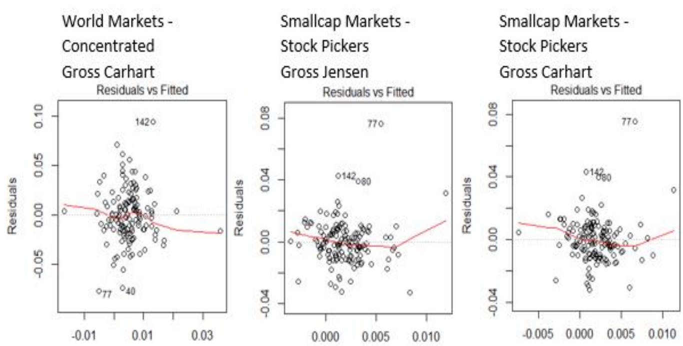
[1]
$$VIF_j = \frac{1}{1 - R_j^2} \tag{D.1}$$
, where R_j^2 is the coefficient of determination for all independent variables[33].

Figure D.2: Testing for linearity and homoscedasticity



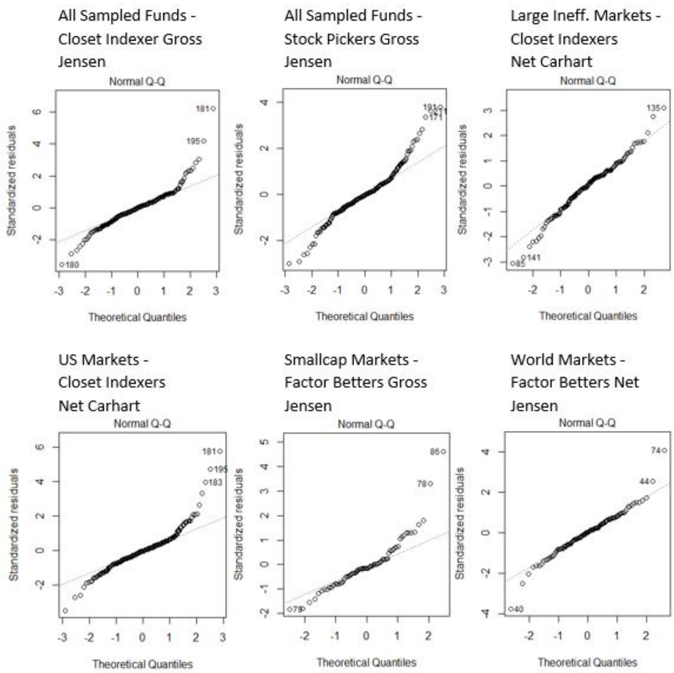
Source: own contribution (computed in R)

Figure D.3: Testing for linearity and homoscedasticity



Source: own contribution (computed in R)

Figure D.4: Testing for normality



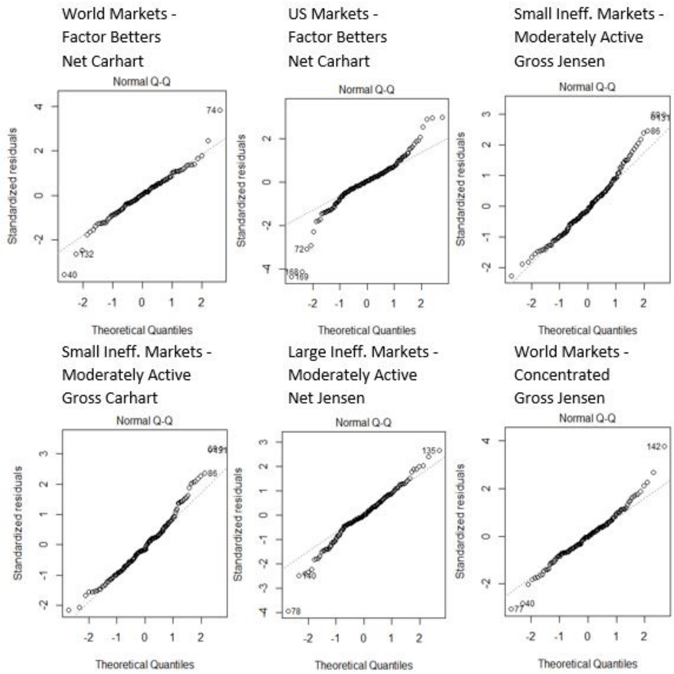
Source: own contribution (computed in R)

level of $\alpha = 5\%$ the null and the alternative hypothesis are stated to be:

- H_0: Error terms are not autocorrelated
- H_a: Error terms are autocorrelated (positive or negative)

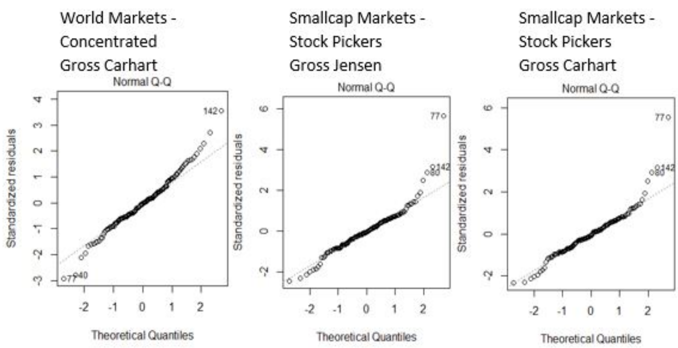
A Durbin-Watson statistic around 2 implies no autocorrelation ($p - value > 5\%$), whereas a significant value below 2 suggests positive autocorrelation, and a significant value above 2 suggests negative autocorrelation[34][33][36]. Table D.1 shows that three of performance models' error terms are autocorrelated, which are 'Smallcap Markets - Factor Betters Gross Jensen', 'World Markets - Factor Betters Net Jensen' and 'World Markets - Factor Betters Net Carhart'. It is further noted that 'Large Ineff. Markets - Moderately Active Net Carhart' has a p-value just below the significance level of 5%. However, since p-value is fairly close being above 5% (by a margin of 0.4%) the autocorrelation assumption for this particular model is assumed to be met.

Figure D.5: Testing for normality



Source: own contribution (computed in R)

Figure D.6: Testing for normality



Source: own contribution (computed in R)

Table D.1: Test of multicollinearity and autocorrelation

Model				Multicollinearity	Autocorrelation	
Market	Group	Gross/ Net	Jensen/ Carhart*	Variance Inflation Factor (VIF)	Durbin-Watson statistics (D-W)	D-W p-value
All Sampled Funds	Closet Indexers	Gross	Carhart	VIF=1.029	D-W stat=2.034	p-value=0.87
All Sampled Funds	Stock Pickers	Gross	Carhart	VIF=1.042	D-W stat=1.847	p-value=0.216
Large Ineff. Markets	Closet Indexers	Net	Carhart	VIF=1.054	D-W stat=2.153	p-value=0.354
US Markets	Closet Indexers	Net	Carhart	VIF=1.044	D-W stat=1.933	p-value=0.596
Smallcap Markets	Factor Betters	Gross	Jensen	VIF=1.044	D-W stat=2.501	p-value=0.016
World Markets	Factor Betters	Net	Jensen	VIF=1.034	D-W stat=2.46	p-value=0.022
World Markets	Factor Betters	Net	Carhart	VIF=1.054	D-W stat=2.45	p-value=0.004
US Markets	Factor Betters	Net	Carhart	VIF=1.089	D-W stat=1.955	p-value=0.752
Small Ineff. Markets	Moderately Active	Gross	Jensen	VIF=1.032	D-W stat=2.115	p-value=0.474
Small Ineff. Markets	Moderately Active	Gross	Carhart	VIF=1.054	D-W stat=2.224	p-value=0.178
Large Ineff. Markets	Moderately Active	Net	Carhart	VIF=1.047	D-W stat=2.331	p-value=0.046
World Markets	Concentrated	Gross	Jensen	VIF=1.019	D-W stat=1.984	p-value=0.91
World Markets	Concentrated	Gross	Carhart	VIF=1.047	D-W stat=2.052	p-value=0.836
Smallcap Markets	Stock Pickers	Gross	Jensen	VIF=1.026	D-W stat=1.98	p-value=0.84
Smallcap Markets	Stock Pickers	Gross	Carhart	VIF=1.031	D-W stat=1.950	p-value=0.742

Note: Red indicate the models, which fail to meet the multicollinearity or the autocorrelation assumptions (no model fail to meet the multicollinearity assumption).

Source: own contribution (computed in R)

APPENDIX E

Appendix E

This appendix includes brief parts of the R-code. All lines of R-code, data files and simulation sheets can be found at:

https://drive.google.com/drive/u/0/folders/0B0aaEVAK-QTCV0ox0ExZZEUxS1E

E.1 Brief Parts of R-code

It should be noted that regression analysis, performed in Chapter 7 and 8, are conducted trough the R package: 'stargazer' developed by Hlavac, Marek (2015), in addition to several other packages listed in the above URL.

```

#-----------------------
#Boxplots for Chapter 4.
#-----------------------

par(mfrow=c(1,3))

#Boxplot for 10 stocks in fund portfolio
  n20 <- c(0.73744387,0.256275647,0.502719922)
  n30 <- c(0.872947948,0.49433867,0.666657851)
  n40 <- c(0.90015459,0.562831899,0.749992093)
  n50 <- c(0.911872054,0.675881633,0.799493487)
  n60 <- c(0.933241636,0.709349388,0.833211669)
  n70 <- c(0.943944699,0.760021188,0.856982048)
  n80 <- c(0.954545912,0.798058731,0.875172817)
  n90 <- c(0.952123864,0.809615256,0.888688299)
  n100 <- c(0.960339013,0.844636368,0.900051408)
  n150 <- c(0.972545959,0.892277161,0.933325787)
  n200 <- c(0.979644185,0.919587782,0.949849719)
  n300 <- c(0.988663372,0.942214723,0.966578881)
  n400 <- c(0.991129154,0.956640378,0.974987995)
  n500 <- c(0.99405103,0.966806861,0.980012935)
  n1000 <- c(0.996426371,0.983582592,0.990013648)

  boxplot(n20,n30,n40,n50,n60,n70,n80,n90,n100,n150,n200,n300,n400,n500,
      n1000,
          las = 2,
          col=c("green","green","green","royalblue2","royalblue2","royalblue2
              ","royalblue2","royalblue2","royalblue2","royalblue2","
```

```
                royalblue2","royalblue2","royalblue2","royalblue2","royalblue2"),
          names=c("20","30","40","50","60","70","80","90","100","150","200","300","400","500","1000"),
          xlab="Number of constituents in benchmark (n)",
          ylab="Active Share (%)",
          main="10 Stocks in Fund Portfolio")

#Boxplot for 40 stocks in fund portfolio
  n40 <- c(0.38153819,0.14347514,0.247967379)
  n50 <- c(0.448536112,0.190092616,0.311258954)
  n60 <- c(0.517291865,0.252194741,0.374798879)
  n70 <- c(0.57043868,0.308244133,0.438842603)
  n80 <- c(0.627200264,0.390161118,0.501128044)
  n90 <- c(0.697872208,0.448750911,0.55571557)
  n100 <- c(0.71295867,0.485467557,0.599988431)
  n150 <- c(0.806814757,0.645146586,0.733336972)
  n200 <- c(0.864786689,0.739411199,0.800048872)
  n300 <- c(0.909125552,0.823803868,0.866648539)
  n400 <- c(0.93229961,0.86481347,0.900033515)
  n500 <- c(0.947245825,0.89333591,0.919983597)
  n1000 <- c(0.973013914,0.947803277,0.960015549)

  boxplot(n40,n50,n60,n70,n80,n90,n100,n150,n200,n300,n400,n500,n1000,
          las = 2,
          col=c("red","red","red","red","green","green","green","royalblue2","royalblue2","royalblue2","royalblue2","royalblue2","royalblue2"),
          names=c("40","50","60","70","80","90","100","150","200","300","400","500","1000"),
          xlab="Number of constituents in benchmark (n)",
          ylab="Active Share (%)",
          main="40 Stocks in Fund Portfolio")

#Boxplot for 10 stocks in fund portfolio
 n100 <- c(0.331312828,0.17839356,0.249148502)
 n150 <- c(0.452614861,0.302672933,0.374895419)
 n200 <- c(0.579100525,0.419561718,0.50053151)
 n300 <- c(0.719318117,0.611416239,0.666631078)
 n400 <- c(0.795216619,0.704804875,0.750003668)
 n500 <- c(0.838173946,0.759990841,0.799999219)
 n1000 <- c(0.92001397,0.880694463,0.899916825)

 boxplot(n100,n150,n200,n300,n400,n500,n1000,
          las = 2,
          col=c("red","red","red","royalblue2","royalblue2","royalblue2","royalblue2"),
          names=c("100","150","200","300","400","500","1000"),
          xlab="Number of constituents in benchmark (n)",
          ylab="Active Share (%)",
          main="100 Stocks in Fund Portfolio")

#-----------------------------------------------------
#Running Pearson's correlation estimates for Chapter 8.
#-----------------------------------------------------
```

```
CorrelationMatrix <- read.csv("PearsonsCorrelation.csv") #Loading
    Correlation data

library(xtable)

corstarsl <- function(x){
  require(Hmisc)
  x <- as.matrix(x)
  R <- rcorr(x)$r
  p <- rcorr(x)$P


  # define notions for significance levels
  mystars <- ifelse(p < .001, "***", ifelse(p < .01, "** ", ifelse(p < .05,
      "* ", " ")))

  # trunctuate the matrix that holds the correlations to two decimals
  R <- format(round(cbind(rep(-1.11, ncol(x)), R), 2))[,-1]

  # New matrix with significance level
  Rnew <- matrix(paste(R, mystars, sep=""), ncol=ncol(x))
  diag(Rnew) <- paste(diag(R), " ", sep="")
  rownames(Rnew) <- colnames(x)
  colnames(Rnew) <- paste(colnames(x), "", sep="")

  # removing upper correlation estimate
  Rnew <- as.matrix(Rnew)
  Rnew[upper.tri(Rnew, diag = TRUE)] <- ""
  Rnew <- as.data.frame(Rnew)

  ## deleting last column and return the matrix
  Rnew <- cbind(Rnew[1:length(Rnew)-1])
  return(Rnew)
}

corstarsl(CorrelationMatrix[,1:11])
xtable(corstarsl(CorrelationMatrix[,1:11])) #Latex code

#-------------------------------------------------------
#Summary Statistics for Variables - 2015, for Chapter 3.
#-------------------------------------------------------
SummaryStatisticsVariables2015 <- read.csv("SummaryStatisticsVariables2015.
    csv") #Loading variable data
stargazer(SummaryStatisticsVariables2015,
          title="Descriptive Statistics - Year 2015",
          median=TRUE,
          covariate.labels=c("Fund Size","Expense Ratio","Turnover",
                              "No. Stocks","Top 10 Holdings",
                              "Cash","Average Market Cap","Manager Tenure"),
          flip=TRUE)

#-------------------------------------------------
#Value at Risk, and Conditional ES for Chapter 7.
#-------------------------------------------------
```

```
#######################
# VaR (Value at Risk) #
#######################

#Group Closet Indexers (gross returns)
mu = 0.00071581
sigma = 0.004484602
alpha = 0.95
VaR.alpha = mu + sigma*qnorm(alpha,0,1)
VaR.alpha

#Group Factor Betters (gross returns)
mu = 0.001029448
sigma = 0.008194849
alpha = 0.95
VaR.alpha = mu + sigma*qnorm(alpha,0,1)
VaR.alpha

#Group Moderately Active (gross returns)
mu = 0.000989328
sigma = 0.008903865
alpha = 0.95
VaR.alpha = mu + sigma*qnorm(alpha,0,1)
VaR.alpha

#Group Concentrated (gross returns)
mu = 0.004458696
sigma = 0.016846265
alpha = 0.95
VaR.alpha = mu + sigma*qnorm(alpha,0,1)
VaR.alpha

#Group Stock Pickers (gross returns)
mu = 0.002949123
sigma = 0.014786035
alpha = 0.95
VaR.alpha = mu + sigma*qnorm(alpha,0,1)
VaR.alpha


############################################
# ES (Expected Shortfall)/ Conditional VaR #
############################################

#Group Closet Indexers (gross returns)
mu = 0.00071581
sigma = 0.004484602
alpha = 0.95
q.alpha.z = qnorm(alpha)
ES.alpha = mu + sigma*(dnorm(q.alpha.z)/(1-alpha))
ES.alpha

#Group Factor Betters (gross returns)
mu = 0.001029448
```

```
sigma = 0.008194849
alpha = 0.95
q.alpha.z = qnorm(alpha)
ES.alpha = mu + sigma*(dnorm(q.alpha.z)/(1-alpha))
ES.alpha

#Group Moderately Active (gross returns)
mu = 0.000989328
sigma = 0.008903865
alpha = 0.95
q.alpha.z = qnorm(alpha)
ES.alpha = mu + sigma*(dnorm(q.alpha.z)/(1-alpha))
ES.alpha

#Group Concentrated (gross returns)
mu = 0.004458696
sigma = 0.016846265
alpha = 0.95
q.alpha.z = qnorm(alpha)
ES.alpha = mu + sigma*(dnorm(q.alpha.z)/(1-alpha))
ES.alpha

#Group Stock Pickers (gross returns)
mu = 0.002949123
sigma = 0.014786035
alpha = 0.95
q.alpha.z = qnorm(alpha)
ES.alpha = mu + sigma*(dnorm(q.alpha.z)/(1-alpha))
ES.alpha

#---------------------------------
#Running Regression for Chapter 7.
#---------------------------------

##############################
#Useful Total Sample Models   #
##############################
library(stargazer)
ModelGroupClosetIndexersGross4 <- lm(ClosetIndexersGross ~ Mkt.RF+SMB+HML+
    WML, data=GroupClosetIndexers)
ModelGroupStockPickersGross4 <- lm(StockPickersGross ~ Mkt.RF+SMB+HML+WML,
    data=GroupStockPickers)

stargazer(ModelGroupClosetIndexersGross4,
          ModelGroupStockPickersGross4,
          title="All Sampled Funds - Closet Indexers and Stock Pickers",
          align=TRUE, model.numbers=FALSE, dep.var.labels.include = FALSE,
              no.space=TRUE,

          dep.var.caption="Benchmark Adjusted Gross Returns",
          column.labels=c("Closet Indexers","Stock Pickers"),
          covariate.labels=c("MKT","SMB","HML","MOM","Alpha"),
          notes = "Estimates are in monthly percentage points",
          omit.stat = c("ser", "f"),
          #type="html",
```

```
          #out="GroupGross4.htm",
          report="vct*") #Generating LaTex output

###############################
#Useful Closet Indexers Models#
###############################
library(stargazer)

ModelClosetIndexersInefficientNet4 <- lm(ClosetIndexersNet ~ Mkt.RF+SMB+HML+
    WML, data=AdjustedInefficientBigMarketsClosetIndexers)
ModelClosetIndexersUSNet4 <- lm(ClosetIndexersNet ~ Mkt.RF+SMB+HML+WML, data
    =AdjustedUSBigMarketsClosetIndexers)

stargazer(ModelClosetIndexersInefficientNet4,
          ModelClosetIndexersUSNet4,
          title="Closet Indexers - Four-factor Model",
          align=TRUE, model.numbers=FALSE, dep.var.labels.include = FALSE,
              no.space=TRUE,

          dep.var.caption="Benchmark Adjusted Net Returns",
          column.labels=c("Large Ineff. Net","US Net"),
          covariate.labels=c("MKT","SMB","HML","MOM","Alpha"),
          notes = "Estimates are in monthly percentage points",
          omit.stat = c("ser", "f"),
          #type="html",
          #out="ClosetIndexers4Net.htm",
          report="vct*") #Generating LaTex output

#-----------------------------------
#Testing assumptions for Chapter 3.
#-----------------------------------

ModelGroupClosetIndexersGross4 <- lm(ClosetIndexersGross ~ Mkt.RF+SMB+HML+
    WML, data=GroupClosetIndexers)
ModelGroupStockPickersGross4 <- lm(StockPickersGross ~ Mkt.RF+SMB+HML+WML,
    data=GroupStockPickers)
ModelClosetIndexersInefficientNet4 <- lm(ClosetIndexersNet ~ Mkt.RF+SMB+HML+
    WML, data=AdjustedInefficientBigMarketsClosetIndexers)
ModelClosetIndexersUSNet4 <- lm(ClosetIndexersNet ~ Mkt.RF+SMB+HML+WML, data
    =AdjustedUSBigMarketsClosetIndexers)

#Testing for linearity, normality and homoscedasticity (non constant
    variance).
#Linearity: There is linearity, if there is no sign of a pattern between the
     residuals and the fitted variables.
#Normality: If the errors/residuals are truly normal distributed the points
    will fall roughly on the diagonal line.
#Homoscedasticity: Resdiuals are free of heterescedasticity if non-constant
    variance is detected (i.e. no megafone shape of the residuals).
plot(ModelGroupClosetIndexersGross4, main="All Sampled Funds - Closet
    Indexers Gross")
plot(ModelGroupStockPickersGross4, main="All Sampled Funds - Stock Pickers
    Gross")
plot(ModelClosetIndexersInefficientNet4, main="Large Ineff. Markets - Closet
     Indexers Net 4 Factor")
```

```
plot(ModelClosetIndexersUSNet4, main="US Markets - Closet Indexers Net 4
    Factor")

#Testing for collinearity for independent variables, i.e. a strong linear
    relationship with either one of the other variables:
#A VIF>10 signal that the model has a colliniearity problem.
VIF(ModelGroupClosetIndexersGross4)
VIF(ModelGroupStockPickersGross4)
VIF(ModelClosetIndexersInefficientNet4)
VIF(ModelClosetIndexersUSNet4)

#Testing autocorrelation for the residuals, a p-value below 0.05 suggests
    autocorrelation, or a value significantly different from 2.
durbinWatsonTest(ModelGroupClosetIndexersGross4)
durbinWatsonTest(ModelGroupStockPickersGross4)
durbinWatsonTest(ModelClosetIndexersInefficientNet4)
durbinWatsonTest(ModelClosetIndexersUSNet4)
```