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Active Share Supported by Tracking Error as Investment Tool for Retail Investors

- An empirical study on funds with different benchmark structures

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Abstract

This report examines whether a retail investor with the use of two measuring tools of active management, active share and tracking error, can increase his expected return by investing into funds with specific investment styles. The methodology is from Cremers & Petajisto (2009), which categorize an active management into either a: Stock Picker, Concentrated Stock Picker, Closet Indexer or Factor Bettor based on Active Share (proxy for stock selection) of their portfolio holding and Tracking Error (proxy for factor bets) of their ex-post returns.

The study includes a sample of 992 funds with 29 different benchmarks in the period 28/02-2003 – 31/05-2015, without making any further decomposing on the sample there is evidence of outperformance by a certain type of management. In the full sample, Concentrated funds generated statistical significant abnormal returns even after adjusted for fees. However, causality was detected between the fund's benchmark structure and the classification of the fund. Thus a numerical model was set up to clarify how active share was affected by an increase in constituents of the benchmark, which showed evidence of a positive relationship. Thereafter all the funds benchmarks were sorted after size and average asset correlation into four equal portfolios, namely: Large Market High Correlation, Large Market Low Correlation, Small Market High Correlation and Small Market Low Correlation, which represent four different investment universes for the funds. The performance evaluation of the four market conditions shows that Cremers & Petajisto (2009) conclusion on outperformance by high active share funds is sensitive to the funds benchmark structure in terms of size. The performance evaluation for the smaller markets differed substantially from Cremers & Petajisto's (2009) findings on active share. In smaller investment universes low active share funds generated significant positive abnormal gross returns in the same extent as high active share funds. Findings on funds in larger investment universes, on the other hand, points towards the use of Active Share and Tracking Error as investment tool for retail investors. Concentrated funds generated statistical positive returns, while Closet Indexers and Factor Bettors generated negative returns after adjusted for fees on larger markets. Thus this thesis suggests that retail investors interpret a fund's active share level conditional of its investment universe, since empirical findings of this paper depends on the fund's benchmark structure.

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1. INTRODUCTION

This section gives an overview of the main motivation behind the development of the problem statement, and furthermore gives the reader a clear picture of the structure behind this thesis.

1.1 MOTIVATIONAL BACKGROUND

Should investors pick active or passive mutual funds is a debate which has been in circulation for almost 50 years, and still is a very hot topic in finance. Basically, the question is whether active investment managers can exploit value in the market that offset the extra fees connected to an investment strategy that is operative more expensive.

The initial of this debate is derived from findings in the 1960's. In 1968 Michael C. Jensen researched active mutual funds' risk adjusted performance and found that these funds on average were not able to beat a buy-and-hold the market strategy. Two years later Eugene Fama published a pioneering work on efficient capital markets, which stated that stocks were priced efficiently and reflected all available information.

In 1974 John C. Boogle founded Vanguard the first index retail fund with the objective of tracking the market and minimizing the operational cost. Now, retail investors had the option to invest their holdings into a fund managed by a passive or active investment strategy.

In 2009 a new dimension to the debate about active versus passive was a reality. Cremers and Petajisto published a new article that differentiated active management into four different management types based on their investment style through a two-dimensional sorting with Active Share (from now on AS) and Tracking Error (from now on TE).

This study caused a new dimension to performance evaluation of active mutual funds. From using a sample average for all active mutual funds there were now several styles of active management and thus different performance measures on active mutual funds. In Cremers and Petajisto (2009), funds with a high level of AS outperformed on average funds with low level significantly. These findings have led to a ripple effect in the investment community, primarily a clash between academics and investment managers.

The findings could be very damaging for some funds since retail investors can exclude the bad apples from the sample by investing through lenses of AS and TE, and this would increase expected average returns to retail investors by preferring this investment strategy.

In the light of Milton Friedman's phrase, frequently used in finance, "There's no such thing as a free lunch," an investment strategy based on such a simple thing as AS and TE should not generate a significant risk adjusted abnormal return.

1.2 PROBLEM STATEMENT

Based on the above introduction the following problem statement is articulated

- ***Will a retail investor investing through the lenses of Active share and Tracking Error unconditional of investment market get higher expected abnormal net returns?***

For ensuring a logical progress in answering the main question, several sub-questions have been made.

1) Are there specific fund managers in the sample, which significantly outperforms in all markets?

2) What are the implications by using AS and TE on different investment markets?

3) Are AS and TE as investment tools for screening funds that outperform the market better to use on some markets than others?

4) Have Stock Pickers outperformed Closet Indexers in risk adjusted abnormal net returns on the different markets?

5) Can a retail investor, who uses yearly AS as investment tool, increase his expected return for the following 5 years?

1.3 DELIMITATION

The research field of this thesis can be narrowed down to if a retail investor can use AS and TE to increase his expected value by investing in a certain type of active management. Several studies have been made in USA with this methodology, and since my interest is if the same findings are observed in markets worldwide, only funds with non-US benchmarks have been included in the data sample.

The methodology used to sort the funds into different types of active management should be simple and easily understandable for the retail investors. Subsequently the approach by Cremers & Petajisto (2009) is preferred over Petajisto (2013).

In the calculations of AS, all the funds are assumed to only invest in stocks within their benchmark index. Hence, cash positions and investments in stocks outside their benchmark are delimitated. Consequently, AS solely represent the fund managers' active bets against a passive index with the same underlying risk, and not because of portfolio holdings outside the benchmark.

In the statistical models some assumptions are made on the parameters where one is that returns are not auto correlated. Empirical research on the subject have found evidence of volatility clustering, but since it is a time consuming and complex problem, the project has assumed returns to be IID and uses unconditional risk adjusted models.

Objective of the study is to explain if the empirical data shows a relationship between AS/TE and outperformance of the benchmark. The study is not trying to explain why the relationship is there, but only if a retail investor can increase his expected return based on empirical data by using AS and TE for investments.

In terms of statistical expressions alpha in this report is being referred to as risk adjusted abnormal returns, where abnormal returns mean benchmark adjusted returns that are the funds returns in excess of the benchmark returns.

For the statistical models used to get risk adjusted abnormal returns some assumptions are made on the parameters. All the models with significant net abnormal returns are further tested in the end of the project for violations of the assumptions, but all models with insignificant net abnormal returns are delimitated from further testing of violations. I admit that some models could be questionable because of violations of the assumptions.

1.4 STRUCTURE

The structure of the report is built on a research design that scrutinizes the sub-questions for answering the main question. The initialized part of the study consists of literature overview, theory, data and methodology sections. In section 5 the whole data sample is analyzed with the presented methodology. In section 6 implications of using the methodology on different markets is described. Section 7 decomposes the sample into four different market types based on a funds benchmark and performance evaluates them with the same methodology. Section 8 investigates the persistence of AS with a risk adjusted model and shows how AS affects dispersion of returns. In Section 9, model diagnostics of the statistical models with significant risk adjusted net abnormal returns are tested for violations of the assumptions made on the parameters in the model.

2. LITERATURE OVERVIEW

In this section literature on some of the most relevant areas for the problem statement are presented. Furthermore, previous findings on active mutual funds are briefly explained.

2.1 ACTIVE VS PASSIVE MANAGEMENT

The ground element of this master thesis is whether an investor can advantageous, in terms of increasing expected returns, invest in an active mutual fund instead of the passive alternative. Thus, a basic knowledge of the difference between active and passive management is necessary.

Active managers' objective is to beat the market they are operating in. Thus, they are spending resources on market research and buying information in the belief that there is value in it. However, buying information and spending hours on market research increase the operational expenses of active management and this leads to higher fees from active mutual funds. The thoughts behind this management strategy is that the value which can be extracted from the market by using extra resources on research and buying information is higher than the cost in extra fees paid by the investor.

Passive management, on the other hand, is only aiming at giving the investor the same returns as the market they are investing in. Thus, these funds are not as operationally costly to run and result in lower fees for the investors.

2.2 FINDINGS ON ACTIVE MANAGEMENT

Findings on the US Market

In the last 50 years, risk adjusted performance studies on active mutual funds have been a common research subject in the financial literature. The first and one of the most well-known works on risk adjusted performance evaluation was made by Michael C. Jensen in 1968, with inspiration from Sharpe (1964), Lintner (1965) and Mossin's (1966) Capital asset pricing model (CAPM). Jensen developed a concept called "Jensen's alpha", which estimated a fund's return with a linear regression on time series data with the CAPM's market portfolio return. Jensen searched for abnormal return in his sample of 115 mutual funds from 1945-1965. His empirical result showed that in average mutual funds underperformed their benchmark with 0.4% before fees and 1.1% after fees. Moreover, he concluded that there was little evidence of any individual fund doing significantly better than expected from mere random chance.

Another study made by Ippolito (1989) used assumptions of Grossman (1976) and Grossman & Stiglitz (1980) that information is costly, and investors buying information should be compensated for this. In his study, Ippolito (1989) used the same methodology as Jensen (1968) except that he assumed a stable beta over time. In Ippolito (1989) alpha was 0.81% on average, where 127 funds had zero alpha, 12 funds had positive alpha and 4 funds negative alpha. Opposite to Jensen (1968), Ippolito (1989) concluded that mutual funds after fees outperformed index funds on a risk adjusted basis. Furthermore, his result showed that mutual funds with higher turnover earned returns sufficiently high to offset the extra charges taken. Elton et al. (1993) pointed out that Ippolito (1989) reached this conclusion due to the performance of non-S&P 500 assets in his data. They argued that once the non-S&P 500 assets were removed, Ippolito (1989) would have reached the same conclusion as previous findings on the subject.

Findings on the European Market

Otten & Bams (2002) conducted a study on equity markets of several European countries and found a general tendency for outperformance of the benchmark among the funds in the sample. Based on a conditional Carhart four-factor model, active mutual funds in four out of five European countries outperformed the benchmark at the 5% significance level in gross returns. The results for abnormal returns were strongest for UK and Italian funds. Conversely, Blake & Timmermann (1998) examined the UK market and found that sample funds on average underperformed the market. Furthermore Cesari & Panetta (2002) found no evidence that Italian equity funds were generating significant abnormal return after fees on average. However, when using gross returns, the authors found a large proportion of funds being able to generate a positive alpha.

2.3 ACTIVE MANAGEMENT WITH FOCUS ON AS AND TE

In their article from 2009, Cremers and Petajisto define active management as any deviation from passive management which is to track an index. Thus, active management is evaluated based on a benchmark index with the same systematic risk exposures as the fund's portfolio.

Since the introduction of Active Share (AS), high focus has been on the use of it as a measuring tool for active management. Investment managers, academics, and researchers have shown great interest in the concept developed by Cremers & Petajisto (2009), since it could be used to predict performance of active managers.

Cremers & Petajisto developed AS since they meant that the use Tracking Error (TE) solely was not good enough to measure active management in general. In their article from 2009, they stated that active management has two value drivers in form of stock selection and factor timing, and TE is more affected by factor timing. Thus, a new concept was needed to support TE which better measured funds that engaged in stock picking activities.

Cremers & Petajisto (2009) conducted the first study on AS, when they researched 2647 US domiciled equity funds in the period 1980-2003 with AS and TE. Cremers & Petajisto (2009) presented four basic types of active management which could be interpreted from the AS and TE level of the fund. The relevance of sorting funds with AS and TE was demonstrated by a two-dimensional sorting with the parameters. Funds were first sorted into five quintiles based on their AS and thereafter into 5 quintiles of TE. Consequently, they got 25 different portfolios that varied in AS and TE level. Furthermore, they used all the equally weighted benchmark adjusted returns from these 25 portfolios as dependent variable in a time series regression with the Carhart four-factor model.

Through this sorting Cremers & Petajisto (2009) found that an increase in AS improved a fund's performance over its benchmark, and there was a significant difference in the benchmark adjusted returns from the highest and lowest quintiles when regressing them with the Carhart four-factor systematic risk factors. On the other hand, Cremers & Petajisto (2009) found no evidence of outperformance by TE, the marginal distribution across all TE quintiles showed consistently negative benchmark adjusted returns and risk adjusted alphas; the switch from the lowest to highest TE quintile even hurt the performance in the lowest AS quintiles.

In May 2012, one of the largest providers of retail index funds, Vanguard, published a study on AS with a different methodology than Cremers & Petajisto (2009) by using an evaluation period from 2001 to 2005 for grouping the funds into four different management types after the Cremers & Petajisto (2009) methodology. Thereafter, they used a performance period from 2006 – 2011 to evaluate the different management types through equally weighted excess returns generated in this period. Conversely to Cremers & Petajisto (2009), Vanguard found no significant evidence that high AS funds outperformed the lower AS funds. Consequently, Vanguard concluded that a high level of AS was not necessary implying a skilled manager that outperformed the market; they furthermore stated that a higher AS leads to a higher dispersion of excess returns.

Petajisto (2013) conducted a new empirical research with an extension of 6 years to the original data of Cremers & Petajisto (2009), which also included the financial crisis. Furthermore, he used a slightly different methodology with five relative quantiles for AS and TE and sliced the data sample into 25 portfolios. In opposition to the original study, Petajisto (2013) included a moderately active management type that were all the 16 portfolios in the middle of the AS and TE quintiles. Closet Indexers were defined as the funds in lowest AS quintile in all except the highest TE quintile. Factor Bettors were the funds in the highest TE quintile in all except the highest AS quintile, which were defined as Concentrated funds. The conclusion was unaffected by extending the data and using a slightly different methodology;

there was still a relationship between a high level of active share and statistical outperformance of the benchmark.

In March 2013 Lazard Asset Management[1] (Hereby referred to as, LAM) conducted a research on AS with focus on international and global funds with Petajisto's (2013) methodology. LAM found evidence of Cremers & Petajisto's statement that high AS funds outperformed low AS funds. Another key point of their study was that investors should take into consideration the investment area of the fund when interpreting AS, since they found a relationship between constituents and weight of the benchmark and the funds AS level. This lead to the fact that funds in smaller investment universes got a natural lower level of AS and thus, LAM recommended that the definition of AS should be re-evaluated downwards on smaller investment markets, since a high AS level would simply not be the optimal solution for the mutual funds in these markets.

In September 2013 a critical study on AS was conducted by American Century Investments[2] (Hereby referred to as, AIC). They pointed out that AS is a rather simplistic measurement of active bets made by the fund manager against the benchmark, but the criteria for producing alpha is manager skills, which cannot be interpreted from a funds' AS level; when used in combination with TE, however, AS could be useful for assessing a fund's investment style. In AIC perspective AS only measures risk relative to the benchmark, from which investors do not benefit. Furthermore, they state that the market volatility (VIX index) is not a constant and thus investors should be aware that the risk of the fund, relative to the benchmark is higher in some periods than others with the same AS level. Moreover, AS is sensitive to benchmark structure and time, which makes investment strategies solely based on AS unreliable. Lastly, AIC states that the value from active trading strategies comes from market inefficiencies that can be replicated by the managers. TE and AS only tells how much the funds are deviating from the benchmark, but not if they are capable of exploiting the market inefficiency.

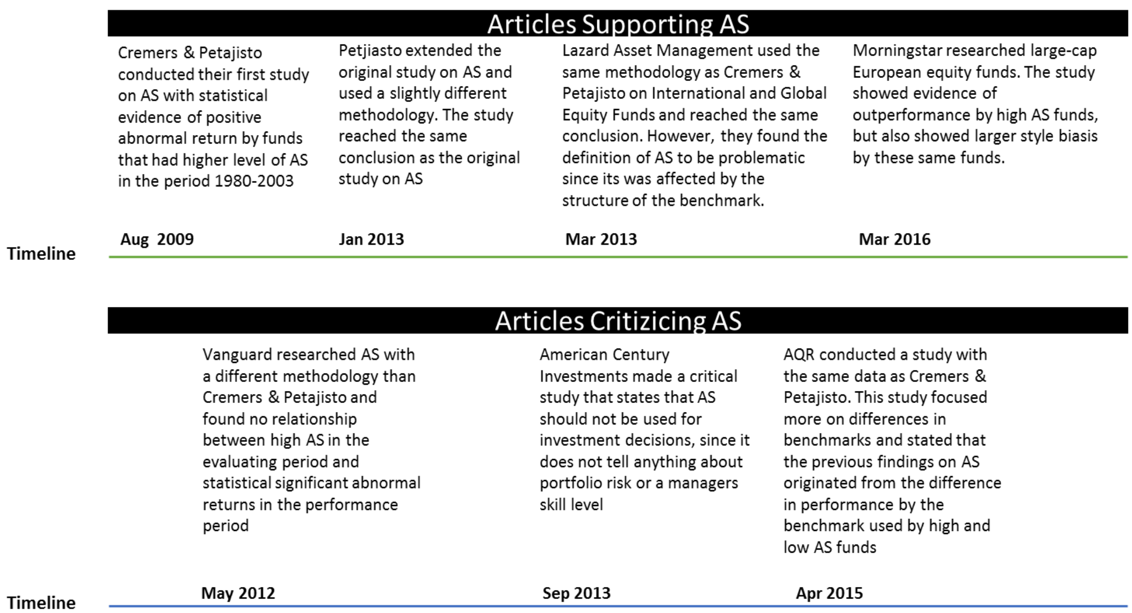
In April 2015 AQR[3] took LAM findings one step further by stating that the conclusion of Cremers & Petajisto (2009) should be seen in the light of benchmark structures being correlated with AS. The study was conducted with the same data as Petajisto (2013) used for his study, but AQR had a much deeper focus on the benchmark types of the funds. They found a tendency that high AS funds were benchmarked to small and mid-cap indices which typically operate in a larger investment universe, while low AS funds had a tendency to be benchmarked to large-cap indices. Thereafter they state that small and mid-cap indices have underperformed in the period that Petajisto (2013) used for his performance evaluation

[1] Written by Erianna Khusainova and Juan Mier
[2] Written by Scott Wittman, Vinod Chandrashekaran and Alex Ornatsky
[3] Written by Andrea Frazzini, Jacques Friedman and Lukasz Pomorski

period in terms of Carhart four-factor alphas. Thus, AQR adjusted their study for the differences in the performance of the benchmark indices attached to the funds in each category. After making this adjustment there was no relationship between a high AS and outperformance of the benchmark. AQR then argued that the findings of Cremers & Petajisto (2009) was not permanent, but rather reflected a time dependent underperformance by large cap indices. However, AQR admit that AS can be used for evaluating mutual fund fees since it measures the activity level by the managers which should be in line with the fees taken by the funds.

In 2016 Morningstar[4] executed a research with foundation in large-cap European equity funds through the lenses of AS. In their study funds in the highest AS quartile in average outperformed funds in the lowest AS quartile. However, one key take-away from Morningstar's research was that funds in the highest AS quartile showed much stronger style biases than the average fund. After controlling for style effects through a Carhart four-factor regression model, Morningstar found that alpha of these funds was lower than for any other group in the most recent five-year period. The increase in a funds level of AS leads to a higher dispersion in returns, and risk levels rise sharply; the worst and best performing funds have high level of AS and thus Morningstar advice investors to use AS in combination with other quantitative and qualitative tools.

FIGURE 1 - TIMELINE OF LITERATURE ON A FEW RECOGNIZED STUDIES ON ACTIVE SHARE



Source: Own Contribution

[4] Written by Mathieu Caquineau, Matias Möttölä and Jeffrey Schumacher part of Morningstar Manager Research

2.4 BENCHMARKS INFLUENCE ON PERFORMANCE EVALUATION

Many researches have studied benchmarks used for performance evaluation on mutual funds. For example, Grinblatt & Titman (1989) point out the problem in setting an appropriate benchmark for market timers, since they switch between a high beta portfolio and a low beta portfolio. Hence, if the funds benchmark only is set to a high beta portfolio, the benchmark adjusted returns will be biased downward. Moreover, Cremers et al. (2013) found that popular benchmarks used for performance evaluation had significant non-zero alphas in both Carhart four-factor model and Fama French three-factor model. For instance, Russell 2000 had an alpha of -2.41 percent[5] from 1980 to 2005. Conversely, S&P 500 had an alpha of 0.82 percent[6]. Moreover, a portfolio that was long the S&P 500 Growth index and short the Russell 2000 Growth index would perform an annual alpha of 5.21 percent[7]. Cremers et al. (2013) states that this is a shocking result when thinking about the fact that the indices are two of the most common benchmarks used by fund managers.

The problem comes from the methodology of risk adjusted models, and this will be specified below:

Methodology of risk adjusted performance evaluation leads to alpha indices:

1. Fama French use equal weighted portfolios for constructing the systematic risk factors, even though these portfolios are based on market capitalization they are very different from each other. This leads to an overweight in the small value portfolio which have outperformed in the period (1980-2005)
2. Carhart and Fama French use CRSP value weighted excess return as market factor[8]. This is a market portfolio proxy of all existing assets in the world[9] - consisting of non-U.S. firms, closed-end funds, REITs, and many other securities. The other assets have dramatically underperformed U.S. common stocks from 1980 to 2005, thus will indices that mainly hold U.S. common stocks, such as S&P500, experience positive alpha values throughout the period.
3. Annual changes of the indexes contribute to negative alphas, principally for small cap indices. For instance, at the end of June, Russell adds and deletes stocks from its indices based on a pre-announced model. This leads to one-time demand shock by index investors, stocks that are added to the Russell 2000 outperform the stocks that are deleted, while the reverse occurs the month after lowering the returns on the index itself. Cremers et al. (2013) find that about one half of the

[5] t-stat of -3.21
[6] t-stat of 2.78
[7] t-stat of 4.23
[8] Market returns provided on Kenneth French's website
[9] Holy grail

negative alpha of the Russell 2000 comes in June and July, suggesting the reconstitution effect also has an impact on indexes alphas.

2.5 PERFORMANCE PERSISTENCE

Whereas the main aim of older research articles has been centered around evaluating fund managers' abilities to create abnormal returns based on forecasting skills, more recent studies add the dimension of testing for persistence. Blake & Timmermann (1998) searched for persistence in the UK market in the period 1972-1995 with 2300 open ended funds. Based on Hendricks et al. (1993) approach, they sorted the funds into quartiles based on their post-ante abnormal performance from the last 24 months. Furthermore, they sorted the funds into four equally weighted portfolios based on their abnormal returns and called the highest quartile the best performers and the lowest quartile worst performers. The holding period was one month and then rebalances was made with the same approach. The experiment was conducted on several different UK equity sectors with the same results, the time series from the portfolio with the best performers generated positive mean abnormal returns, while the worst performers generated negative abnormal return. Carhart (1997) examined 1892 equity funds, which totally accounted for 16109 fund years with his own risk adjusted model (further specified later). Carhart (1997) used Fama French (1992) three factor model with a momentum anomaly to account for short term persistence on the market (performance last 11 months). Carhart found that there was persistence in significant negative abnormal returns within the lowest deciles, while the highest deciles generated insignificant abnormal returns.

Another approach was used by Malkiel (1995) that studied mutual funds persistence based on using a median fund to define a winner and a loser. In his study Malkiel found evidence on persistency among both winners and losers. Hot hands (win followed by a win) occurred more often than a win followed by a loss. Malkiel (1995) found evidence of cold hands as well. However, Malkiel (1995) found no evidence of long term outperformance of top performing funds. He tested a sample of the top 20 funds during the 1970's on returns in 1980's, and found that they underperformed both the overall fund average and the S&P 500 index on average.

In 2016, Morningstar conducted a research on AS and further investigated if there was any performance persistence in AS. The structure of their research was to sort funds into AS quartiles at year t and then estimate the performance of each quartile in the following five-year period lagged with two quarters for ensuring a realistic setup on when the investor had the necessary portfolio information. This approach was made on a rolling basis from 2006 to 2015 and concluded that in four out of five five-year periods funds in the highest AS quartile outperformed all the other quartiles. Conversely, funds from the lowest AS quartile were the worst performers in all the five-year periods.

2.6 RISK ADJUSTED MODELS

The following section includes a brief interpretation of literature on risk adjusted performance models, which is not a part of the theoretical chapter.

Fama French three-factor-model

In 1992 Fama and French introduced a new risk adjusted model with two new parameters based on empirical investigation of the average return observed in the market. Their study was not a risk adjusted performance evaluation study of mutual funds, but rather a critical study of the low explaining power CAPM had on stocks average return. However, their work will be presented since the model has been the foundation on many risk adjusted performance evaluations.

Fama & French (1992) found that based on data from 1963-1990 the CAPM was not able to predict average return well enough. Furthermore, they found that the errors of CAPM were systematic, that the model was negatively biased on a group of assets, while positively biased to another group.

Earlier empirical research had shown that there were many anomalies to the CAPM model, so Fama & French (1992) made a research testing all anomalies to find a better model.

In the search for a better model Fama & French (1992) included some extra regression variables and found that Size and Book to market ratio (BM/ME) had significant influence on average stock returns.

The negative correlation between size and systematic risk is based on a higher probability that small firms will experience liquidity problems than large firms. Hence, investors want a risk premium for holding small companies which leads to higher returns for small companies than for big companies[10].

The positive correlation book-to-market ratio has on systematic risk should be seen in the light of the fact that low BE/ME[11] firms are judged with high prospects, while high BE/ME[12] firms are judged with low prospects by the market. This results in investors demanding higher average returns for value stocks since the risk is higher[13].

Fama and French conclude from the following that small cap stocks and value stocks ceteris paribus should be riskier than large cap and growth stocks, which is reflected in the higher average return for the stocks. Fama & French (1992) concluded that there are more risk factors than market risk affecting stock returns, which lead to the Fama French three-factor model interpreted below

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[10] SMB factor
[11] Growth stocks (High profitability firms)
[12] Value stock (Low profitability firms)
[13] HML factor

$$R_{it} - RF_t = \alpha_i + \beta_{i1}(R_{mt} - RF_t) + \beta_{i2}SMB_t + \beta_{i3}HML_t + \varepsilon_{it} \quad (1)$$

Carhart Four – factor model

In 1997 Carhart wrote an article *On Persistence in Mutual Fund Performance*, where he estimated pricing errors on 27 quantitatively-managed portfolios with Fama French three factors and a lagged factor which accounted for prior year winners and losers. Carhart (1997) found that the Fama French model had systematic positive and negative errors in predicting average return based on how the portfolio had performed in the prior 11 months. The finding confirmed Jegadeesh & Titman (1993) study on short-term momentum tendency – best performers in the prior months also have a tendency to outperform the market in the subsequent months, while opposite for worst performers.

Based on the above findings Carhart (1997) extended Fama & French (1992) three-factor model with a fourth factor, momentum, which incorporated the performance of the asset in the last 12 months compared to the market[14].

Carhart Four-factor model presented below

$$R_{it} - RF_t = \alpha_i + \beta_{i1}(R_{mt} - RF_t) + \beta_{i2}SMB_t + \beta_{i3}HML_t + \beta_{i4}WML + \varepsilon_{it} \quad (2)$$

[14] WML factor

3. THEORETICAL FOUNDATION

The purpose of this section is to provide an overview of the main theoretical themes employed in this study. The section is built up according to a logical structure for introducing the theory used throughout my thesis.

3.1 CAPITAL ASSET PRICING MODEL

Economists from the first half of the 20th century had difficulties in developing an asset pricing model, since the psychological part of risk is hard to incorporate in any model – some people are risk averse, other risk neutral and some even risk lovers.

Harry Markowitz found a solution to this problem by assuming investors are rational mean variance optimizers. Markowitz laid the foundation for the development of the first Capital Asset Pricing Model (CAPM). Sharpe (1964), Lintner (1965) and Mossin (1966) developed CAPM through a set of assumptions about the investors and the market

For the individual investors the assumptions are as follows: 1) All investors are rational and mean variance optimizers. 2) Investors planning horizon is a single period. 3) All investors have homogenous expectations (identical input list).

For the market there are the following assumptions: 1) All assets are publicly held and trade on public exchanges, short positions are allowed, and investors can borrow or lend at common risk-free rate. 2) All information is publicly available. 3) No taxes. 4) No transaction costs.

An investor can replicate all risky assets through either borrowing or investing in the risk-free rate and buying the market portfolio. The assessment of risk in the CAPM universe is a beta parameter that quantifies the sensitivity of the assets to the market portfolio. A risky asset with a β higher than 1, means the investor must borrow money in the risk-free rate and invest them in the market portfolio. On the other hand, if β is lower than 1, the investor should use an asset allocation investing both in risk free rate and the market portfolio.

In the CAPM universe there are two types of risk, firm specific and market risk. The market portfolio only contains market risk, since the firm specific risk is diversified away. From a no arbitrage argument, investors can only demand return for the market risk an asset contain[15]. Otherwise, an investor could set

[15] Beta

up an arbitrage investment strategy by going short in the overvalued asset and going long in the replicating portfolio.

The replication line of the CAPM is called SML, where the intercept is the risk-free rate and the slope is how expected return from a risky asset increase with beta[16] in the CAPM universe.

CAPM formula:

$$E[r_i] = r_f + \beta_i(R_m - r_f) \tag{3}$$

3.2 FAMA FRENCH FIVE-FACTOR MODEL

The newest risk adjusted model is developed by Fama and French (2015) since they found their Fama and French (1992) model used a proxy factor instead of the two "true" underlying risk factors. The value factor (HML) in Fama French (1992) three factor model explained a bit of the profitability and investments factors.

The profitability factor is exploited by buying robust and selling weak profitability stocks, while the fund that want to collect risk premium in the investment factor buys conservative and shorts aggressive stocks in this matter.

The evidence of the risk factors is demonstrated with the Dividend discount model (also known as Gordon's Growth Model). That states that the market value of the firm can be valuated with the sum of all its future dividend payments, discounted back to their present value.

$$m_t = \sum_{\tau=1}^{\infty} E(d_{t+\tau})/(1+r)^{\tau} \tag{4}$$

m_t *is the share price at time t*, $E(d_{t+\tau})$ is the expected dividends in period t *to* τ *and* r *is the internal rate of return on expected dividends.*

The equation (4) states that if two firms have equal d_t, but different share prices, the stock with the lower price has a higher r on expected dividends. Thus, if pricing is rational, the future dividends of the stock with lower price must have a higher risk.

With some fireworks, it is possible to extract the same implications of equation (4) to the relation between expected return, and expected profitability, expected investments, and B/M. Miller and Modigliani (1961) show with some rewritings that the market value implied at time t can be stated as

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[16] $\beta_i = \frac{Cov(r_i, r_m)}{\sigma_m}$

$$M_t = \sum_{\tau=1}^{\infty} E(Y_{t+\tau} - dB_{t+\tau})/(1+r)^{\tau} \tag{5}$$

$Y_{t+\tau}$ is the total equity earnings for period $t+\tau$ and $dB_{t+\tau}$ is the change total book equity in the period.

By dividing equation (5) with total book equity in time, we get an expression known from Fama French (1992) three factor model. The HML key-ratio which is used when sorting funds into value and growth portfolios for determining the factor spread.

$$BookToMarket\ Ratio = \frac{M_t}{B_t} = \frac{\sum_{\tau=1}^{\infty} \frac{E(Y_{t+\tau} - dB_{t+\tau})}{(1+r)^{\tau}}}{B_t} \tag{6}$$

Three statements are made, which explain why average return of the stock is correlated with a firm's profitability and investments.

1) Hold everything constant except the current value of the stock, M_t, and the expected stock return, r. Then a lower value of M_t or equivalently a higher B/M ratio, implies a higher expected return.
2) Hold everything constant except expected future earnings and the expected stock return. Equation (6) then tells us that higher expected future earnings imply a higher expected return.
3) When holding B_t, M_t and expected earnings constant, higher expected growth in book equity – investments – implies a lower expected return.

The 3 statements above show that Profitability and Investments have influence on average expected returns. These findings combined with evidences from Novy-Marx (2010) on Profitability and Aharoni et al. (2013) on Investments as significant parameters for explaining average return led to Fama French's (2015) motivation for augmenting the Fama French (1992) three-factor model.

3.3 POWER OF DIVERSIFICATION

One of the most famous findings in modern finance is capital allocation between risky assets. By using the covariance matrix in an investment decision, an investor can maximize his returns to a specific standard deviation.

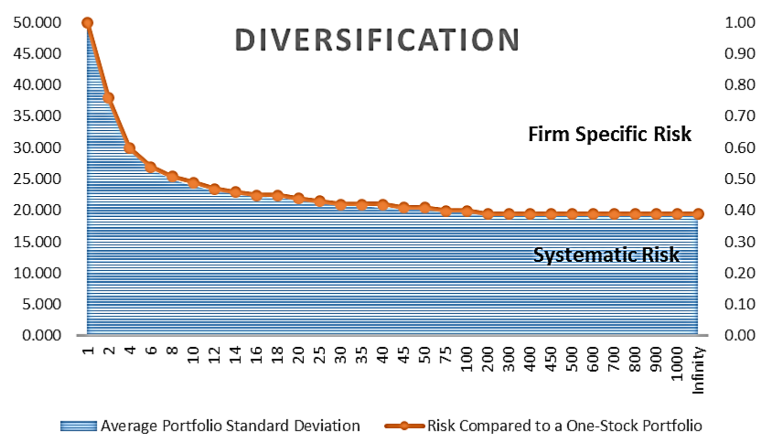
A criterion for using portfolio theory to maximize portfolios return relative to its standard deviation is that the correlation between the assets in the model is lower than 1, not perfectly correlated. In the case of perfect correlation, diversification will not increase returns or lower standard deviation.

Stocks on the financial markets are not perfectly correlated, and therefore the assumption that investors use modern portfolio theory as investment tool have been implemented to all the asset pricing models, CAPM, Carhart Four-Factor and Fama French Five-Factor.

The logic behind the benefits for the investor from diversifications is that stock includes two types of risk, systematic risk and unsystematic risk. The unsystematic risk is related to the specific company, and the investor can by diversification decrease the effect which firm specific news has on his portfolio. Firm specific news for Pandora – low sales growth in China – is not affecting Carlsberg's stock price. On the other hand there is systematic risk which affects all the stocks, which cannot be diversified away. A rise in the oil price, FED increasing the interest rate, or the collapse of Lehmann Brothers.

Empirical studies have been performed on the effect of standard deviation to increasing the number of assets in a portfolio. Statman (1987) performed a research on NYSE stocks where he increased the number of stocks at the portfolio and researched how this affected the average standard deviation of portfolios composed.

FIGURE 2 - SHOWS THE EFFECT DIVERSIFICATION HAS ON A PORTFOLIOS AVERAGE STANDARD DEVIATION WITH STOCKS LISTED ON NYSE



Source: Own Contribution [Numbers from Statman (1987)]

The risk is decreasing when more stocks are added to the portfolio – thus diversification is the closest an investor comes to a free lunch. The investor gets almost all the benefit from diversification by buying 20-30 stocks, so investing without holding a portfolio is from a risk adjusted perspective value destroying.

Most investors have some wealth constraints, and buying your own portfolio of stocks is expensive. Furthermore, a basic understanding of portfolio theory is necessary for making the optimal asset allocation, which is more than most regular people possess. Consequently, investing in mutual funds has been a popular choice for the average investors, since buying a share of the mutual fund gives the investors a share in a diversified portfolio.

3.4 ACTIVE MANAGEMENT

In his article Fama (1972) describe value creation from active managers to come either from skills in stock selection or in market timing. In Cremers & Petajisto (2009) active management is boxed after their exposure to these two tools for value creation. In their terminology, AS and TE are used to quantify the strategic approach by the management.

The objective of an active manager is to beat his benchmark, subsequently Cremers & Petajisto (2009) use the benchmark to estimate the activeness of the manager. AS quantifies the manager's active bets on stock selection against the benchmark, while TE quantifies his active bets on systematic risk factors.

All the funds are grouped after their active bets against the benchmark.

1) Stock Pickers has a high AS, but low TE **2)** Concentrated has both high AS and TE.
3) Closet Indexers has low AS and low TE **4)** Factor Bettors has low AS, but high TE.

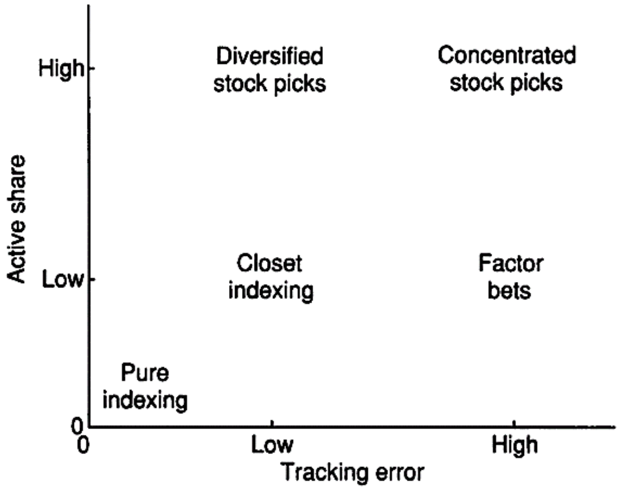
For giving a deeper understanding of Cremers & Petajisto (2009) terminology a brief explanation of how AS and TE will be in general for two active mutual funds with different investment approach. Fund A) Is a highly active fund that invest with a bottom-up approach. Fund B) Is also highly active, but use a top-down investment approach.

Fund A) investment strategy is based on increasing weights of stocks in their portfolio with higher intrinsic value than expected by the market. Opposite, the fund is decreasing weights in stocks with lower intrinsic value than expected by the market.

Fund A) is highly active, but the investments are solely based on estimation of the market value. Consequently, a portfolio from a fund with this investment strategy will normally be spread out over many sectors in the market and thus the portfolio will be highly correlated with the benchmark. In terms of AS and TE, this means that the fund has a high AS, but low TE.

Fund B) investment strategy depends on finding sectors that will outperform the market and increase the weights of assets in those sectors. Consequently, the portfolio is not well-diversified, since assets from the same sector are highly correlated. With the methodology in Cremers & Petajisto (2009) this fund would have a high AS and a high TE.

FIGURE 3 - ILLUSTRATION OF DIFFERENT TYPES OF ACTIVE MANAGEMENT



Source: Cremers & Petajisto (2009)

The new two-dimensional sorting has made it possible to differentiate active management. Previous written literature on the subject was mostly based on arithmetic average gross and net returns from active funds. Examples of this can be found in Jensen (1968) and Ippolito (1989), which base their performance evaluation on average numbers of the total sample.

AS and TE has contributed to the discussion of active versus passive mutual funds by differentiating active funds into different management styles, and gives the investors an intuitive tool to evaluate the fairness of the fees taken by the mutual fund (compared to the active risk).

Measures of Active Management

In the past years TE has been used for measuring active portfolio management. TE is described in Grinold & Kahn (1999) as the volatility between a fund's return and its benchmark return. The interpretation of TE is given by

$$Tracking\ Error = Stdev\left[R_{fund,t} - R_{index,t}\right] \tag{7}$$

Many active managers aim for high returns, but want a low tracking error, so there is a smaller chance of significantly underperforming the benchmark and getting an outflow of money from unsatisfied investors.

The newest tool for evaluating active management is active share, which quantifies how active a management is comparing the holdings of mutual funds with the holdings of its benchmark index.

$$Active\ Share = \frac{1}{2}\sum_{i=1}^{N} |\omega_{fund,i} - \omega_{index,i}| \tag{8}$$

Where $\omega_{fund,i}$ and $\omega_{index,i}$ are the portfolio weights made in each asset by the fund and the benchmark. AS is a measuring tool for the active stock selection made by the fund compared to the benchmark measured in absolute terms. When measured in absolute terms both a decrease and increase in weight on an asset from the benchmark will be an active bet from the management.
Subsequently a fund could theoretically deviate with 200 percent from the benchmark. Consequently, the total sum of difference in portfolio weights is divided by two for getting AS.

For a simplistic illustration of AS, let us consider a fund with a $100 million portfolio benchmarked against MSCI Europe. Imagine first a $100 million investment in the index, now the fund is an index fund holding 448 stocks. After a market research the manager only sees value in half of the index, so he sells the other part from his portfolio, generating $50 million which he invests in the stocks he believes in. This produces an AS of 50 percent (i.e., 50 overlap with the index)

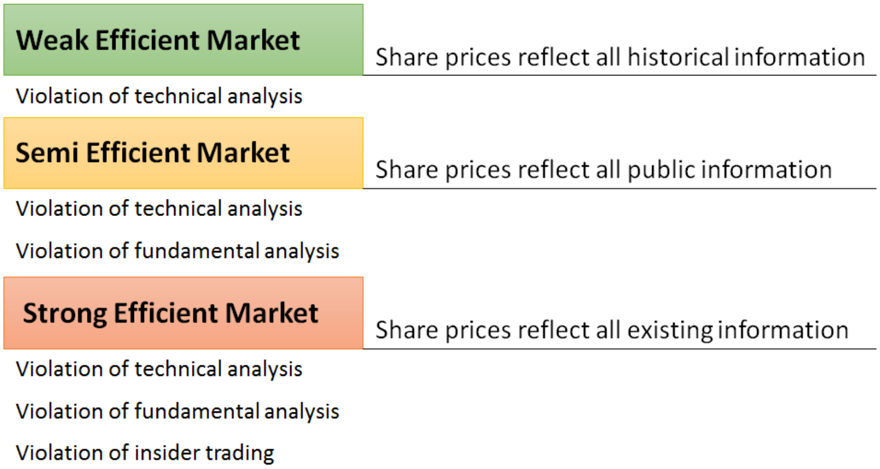
3.5 EFFICIENT MARKET HYPOTHESIS

Early time series analyses in the 1950's on stock prices showed that patterns were totally random and could not be predicted by a model Bodie et al. (2014). The findings shocked academics and no one could explain why stock patterns were random.

Later Fama (1965) developed a theory on efficient markets. The randomness of the stock patterns reflects an efficient market, where all existing public information is included in the valuation of the company, and the stocks therefore only evolve through new random information. In the case that stocks were predictable through a forecasting model, institutional investors would immediately start trading the overvalued/undervalued stocks, which would make the stocks reach a new equilibrium price based on these forecasts.

The efficient market hypothesis (EMH) is one of the most used arguments against active portfolio management, since stock prices are random, a portfolio manager cannot deliver abnormal returns.

In a later article on the subject Fama (1970) defined three different forms of EMH:



Source: Own Contribution [inspired by Fama (1970)]

Of the three forms of EMH, the most realistic form in European equity markets is arguably semi efficient. The semi efficient form has been tested by many researchers which have found evidence for it. For example, Fama et al. (1969) found that the firm's future dividend payment was on average already fully reflected in the price of a split share at the time. Many similar studies have been made, all reaching the same conclusion on market efficiency.

The strong efficient market, however, is quite extreme and does not reflect the stock price on the financial market. Trading based on Insider information can be made profitable.

The EMH is basically the cornerstone in the passive versus active funds debate, since active funds take higher fees, ceteris paribus, they must deliver positive abnormal returns, which is a violation of the efficient market.

The paradox of the EMH is that if all investors accepted that the market was efficient and bought and sold without doing any research, then the market would become inefficient. The efficient market needs active investors buying and selling stocks based on fundamental analysis.

When evaluating a larger sample of funds, the risk of them differs, when using risk-adjusted models they become comparable in terms of their performance. There are many different approaches to adjust for risk, but in this report risk-adjusted evaluations are performed with Jensen's (1968) alpha, Carhart's (1997) four-factor model and Fama French's (2015) five-factor model.

3.6 RISK ADJUSTED PERFORMANCE MEASURES

Jensen's alpha

Jensen's alpha is a linear regression of

$$R_{it} - RF_t \; = \; \alpha_i + \beta_i(Mkt_t - RF_t) + \varepsilon_{it} \tag{9}$$

Where R_{it} is the funds return at time t *and* RF_t is the risk-free rate. This should be equal to the excess returns of the market portfolio multiplicated with β_i that estimates the market sensitivity of the assets of the fund and an intercept α_i that made Jensen's (1968) article famous. The intercept is used to evaluate the risk-adjusted performance of the fund, where funds with statistical significant α_i>0 are outperforming the market, while the opposite is true for α_i<0.

Since the introduction of CAPM there have been published several models based on return anomalies example of this is Fama French (1992), Carhart (1997) and Fama French (2015). This leads to risk adjusted models that have higher explanatory power and thus define a part of the intercept from Jensen's alpha model as a funds exposure to these anomalies.

Carhart's four-factor alpha

Carhart (1997) risk adjusted performance model besides the market portfolio also takes into account a fund's portfolio exposure to small stocks, value stocks and previous outperforming stocks.

$$R_{it} - RF_t \; = \; \alpha_i + \beta 1_i(Mkt_t - RF_t) + \beta_{2i}(SMB) + \beta_{3i}(HML) + \beta_{4i}(WML) + \varepsilon_{it} \tag{10}$$

β_{2i} estimates the sensitivity of the fund's portfolio to the spread in returns between small and large stocks (SMB). β_{3i} estimates the sensitivity of the fund's portfolio to the spread in returns between value stocks (High book-to-market ratio) and growth stocks (Low book-to-market ratio) (HML).β_{4i} estimates the sensitivity of the fund's portfolio to the spread between winners and losers in terms of stocks based on the spread in returns from the last 11 months (WML)

Fama French's five-factor alpha

The newest risk adjusted model from Fama French (2015) adds two risk anomalies in terms of profitability and investments besides Fama French's (1993) three-factor model.

$$R_{it} - RF_t \; = \; \alpha_i + \beta 1_i(Mkt_t - RF_t) + \beta_{2i}(SMB) + \beta_{3i}(HML) + \beta_{4i}(RMW) + \beta_{5i}(CMA) + \varepsilon_{it} \tag{11}$$

The first three β in the equation are the same as in Carhart's four-factor model above. Additionally β_{4i} estimates the sensitivity of the fund's portfolio to the spread in returns between robust and weak stocks in terms of profitability (RMW). β_{5i} estimates the sensitivity of the fund's portfolio to the spread in returns between conservative and aggressive stocks in terms of investments.

4. DATA AND METHODOLOGY

This section gives an insight into the engine room of this master thesis. Firstly, presenting the selection criteria on the data and calculations of Active Share and Tracking Error. Hereafter, an introduction of the toolbox in form of methodology and risk adjusted performance models.

4.1 DATA

All mutual fund data used in this thesis was obtained from Morningstar Direct database and covers 148 monthly observations of time series of fund returns, 02/2003 – 05/2015. In the data, I have also included obsolete funds for limiting survivorship bias in the dataset. Furthermore, I have collected data from all the benchmark indices through Datastream[17].

An essential part of this performance analysis is delimitations, since the mutual fund industry is very large and consists of many different types of funds. In the delimitations my focus point has been to clean the data, so only comparable funds are left.

Selection criteria:

I. The fund is an open-ended equity mutual fund.
II. The fund is for retail investors.
III. The fund is characterized as active.
IV. The fund must have at least $10,000,000 in assets under management.
V. The fund must have portfolio holdings of minimum 6 months, with matching returns.
VI. The fund's benchmark is a MSCI index.
VII. The fund's investment area is geographical and outside US.
VIII. The fund's benchmark has 10 constituents or more.
IX. The fund's benchmark has no investment style.

Sample

After selecting funds that fulfilled the criteria, 992 funds with investment mandate in the listed markets below were left.

[17] Datastream is a historical database with about 25 million different time series on financial data from Thomson Reuters.

TABLE 1 – OVERVIEW OF FUNDS BENCHMARK IN THE DATA

MSCI Regional Index			
Developed Markets	**Emerging Markets**	**Developed & Emerging Markets**	**Frontier Markets**
Europe	EM Europe	ACWI Ex USA	Frontier Markets
Europe Ex UK	EM Latin America	AC Asia Pacific	
EMU	BRIC	AC Asia Pacific Ex Japan	
Nordic Countries		AC Asia Ex Japan	
MSCI Country Index			
Asia	**America**	**Europe**	**Pacific**
China	Brazil	Denmark	Australia
India		Italy	Hong Kong
Indonesia		Poland	Japan
Korea		Russia	
Thailand		Spain	
		Sweden	
		Switzerland	
		Turkey	

Source: Own contribution (With inspiration from MSCI market classifications)

The funds in total gave 92680 monthly observations.

TABLE 2 – OVERVIEW OF FUNDS COVERAGE FROM 10 RANDOMLY SELECTED COUNTRIES

Investment Area	Brazil No of Funds	Denmark No of Funds	Hong Kong No of Funds	India No of Funds	Italy No of Funds
Morningstar Raw Dataset	632	30	12	113	42
Fullfilling Selection Criteria	**5**	**28**	**7**	**43**	**33**
Percentage of funds in sample	**1%**	**93%**	**58%**	**38%**	**79%**
	Korea No of Funds	**Russia** No of Funds	**Spain** No of Funds	**Sweden** No of Funds	**Switzerland** No of Funds
Morningstar Raw Dataset	**783**	**31**	**64**	**94**	**139**
Fullfilling Selection Criteria	**7**	**28**	**18**	**39**	**69**
Percentage of funds in sample	**1%**	**90%**	**28%**	**41%**	**50%**

The Morningstar Raw Dataset is from 31/05/2015

Source: Own contribution

Choice of Benchmark

The choice of benchmark is a vital part of the performance evaluation, since fund returns are compared with its benchmark. A benchmark should reflect a fund's portfolio risk characteristic to determine if the fund delivers abnormal returns. Thus, choosing a wrong benchmark has an impact on the performance evaluation and will affect the conclusions. In my Master thesis, the funds benchmark is used as selection criteria and furthermore later used for sorting the fund into a market peer group.

For minimizing the principal agent problem in choice of benchmark[18], my analysis builds on benchmark set by Morningstar onto each fund. Morningstar is independent of the principal agent conflict and sets a benchmark based on the fund's risk characteristics.

Active Share

AS has been calculated through Morningstar Direct on a rolling monthly basis, starting from the fund's first reported portfolio holding date in the observed time frame. To calculate AS, both portfolio and benchmark holdings are necessary. However, through Morningstar Direct it is possible to obtain AS values from the examined 12-year period.

The clear majority of funds in the sample only file their portfolio holdings quarterly. This means that AS in the months in-between are only influenced by the stock positions and not by investment strategies (buying and selling stocks).

The AS calculation is based on the same benchmark through all the time frame; this could potentially bias the performance evaluation, but I somehow account for this by excluding funds which have switched benchmark over the examined 12 years.

Only funds with AS values in the range between 1 and 99 percent are included in the sample. A fund with an AS higher than 99 percent is excluded because this indicates a misleading benchmark set to the fund, since an AS close to 100 is almost impossible. Furthermore, a fund with AS less than 1 percent is excluded since this indicates an index fund.

Tracking Error

The annualized ex-post tracking error has been calculated through Morningstar Direct, for each month based on daily gross fund returns. It is calculated based on rolling 180 daily observations, starting 31/08/2002, to get the standard deviation of the funds' excess returns at the end of each month.

4.2 METHODOLOGY

In order to evaluate the performance of the four different groups of active management I take an approach inspired by Cremers & Petajisto (2009), where funds are allocated into four different portfolios of active management: Stock Picking, Concentrated, Closet Indexing and Factor Bets.

The portfolios are constructed by using an absolute limit to distinguish between low and high AS and a relative limit to distinguish between high and low TE for the funds.

[18] Funds managers' tendency to select a benchmark that they outperform

TABLE 3 – METHODOLOGY USED IN THIS THESIS

Active Share / **60%**	**Trackin Error** Low	**Median**	**Trackin Error** High
High	**Stock Picker**		**Concentrated**
Low	**Closet Indexer**		**Factor Bettor**

Source: Own contribution [inspired by Cremers & Petajisto (2009)]

The funds are allocated to one of the four portfolios each month, and this means that the sorting is dynamical and allows funds to switch in the period. After the funds are allocated into the four different types of active management, as illustrated in table 4, they are matched with their benchmark adjusted returns (Hereafter referred to as abnormal return). Thereafter, the equally weighted average of the monthly abnormal return for each active management type is calculated in the period [02/2003 - 05/2015]. Consequently, there are four different time series of excess return with 148 observations that represent the performance of each management type.

For risk adjusting the abnormal return, I use two traditional performance models: Jensen's alpha (Eq.9) and Carhart's four-factor (Eq.10). Furthermore, I use the new Fama French five-factor model (Eq. 11). Most weight is put into the results of the Fama French five-factor model, since it has found new risk anomalies to the other models. Carhart is used in this report mainly because of the momentum anomaly, which is not part of Fama French's new model, and Jensen Alpha is used in order to be able to compare it with historical results in the risk adjusted performance literature. The regression models are either constructed by equally weighted portfolios of abnormal gross or net return calculated from geometric time series of funds as dependent time series variable, and risk factors from the performance models as independent time series variables.

The most vital part of this master thesis is the t-statistics of the H_0 hypothesis on the intercept (Hereby referred to as risk adjusted abnormal return) in the regression setting. If H_0 is rejected when using a two-sided confidence interval on 95 percent, the management type can outperform their benchmark even when adjusting for systematic risk factors.

4.3 STATISTICAL MODELS

After all the funds in the data sample are sorted with the methodology of Cremers & Petajisto (2009), the next step is to analyze the equally weighted time series abnormal return data from the different management types with statistical models.

The data used in these statistical models consist both of internal data, time series abnormal return data from Cremers & Petajisto (2009) methodology and external data downloaded from Kenneth French's data library [1]. The internal data was thoroughly explained in the methodology section, therefore only the external data will be explained here.

Kenneth French has through empirical data, computed monthly discrete time series returns for betting on systematic risk factors of the asset pricing models. In his data library are different versions of the factor models, all after which region is analyzed. In this report there are funds scattered worldwide excluding US performance evaluated, thus Global Ex US version is used since the factors best represent the funds in the data sample.

In the subsequent paragraph is a short demonstration of how the factors, which are recurring in the performance evaluation, are computed. The market portfolio from the model is the regions value weighted market return minus the U.S. one-month T-bill rate. The SMB factor is the difference in average returns of an equal weighted portfolio consisting of Small Value, Small Neutral and Small Growth firms and an equal weighted portfolio of Big Value, Big Neutral and Big Growth firms. The HML is the difference of average returns of two equally weighted portfolios one with Value firms[19] (High B/M) and one with Growth firms[20] (Low B/M).

Insight into the regression setting

The regression models are presented as

$$AbnormalReturn_{it} = \alpha_i + \beta 1_i(Mkt_t - RF_t) + \varepsilon_i \tag{12}$$

$$AbnormalReturn_{it} = \alpha_i + \beta 1_i(Mkt_t - RF_t) + \beta 2_i(SMB_t) + \beta 3_i(HML_t) + \beta 4_i(WML_t) + \varepsilon_i \tag{13}$$

$$AbnormalReturn_{it} = \alpha_i + \beta 1_i(Mkt_t - RF_t) + \beta 2_i(SMB_t) + \beta 3_i(HML_t) + \beta 4_i(CMA_t) + \beta 5_i(RMW_t) + \varepsilon_i \tag{14}$$

[19] $\frac{1}{2}(Small\ Value + Big\ Value)$

[20] $\frac{1}{2}(Small\ Growth + Big\ Growth)$

Dependent variable

As explained earlier the abnormal returns are defined as

$$R_{benchmark-adjusted,t} = R_{fund,t} - R_{benchmark,t} \tag{15}$$

The abnormal return should represent the marginal effect of the active management strategy, since the funds benchmark index represent a passive management with the same underlying risk.

$$R_{fund,t} = \frac{(NAV_t - NAV_{t-1}) + CapitalGainDistribtuion}{NAV_{t-1}} \tag{16}$$

The monthly return of the fund in March is computed from the marginal change in NAV (Net Asset Value) from (Ultimo February, $_{t-1}$) to (Ultimo March, $_t$) including all reinvested capital in the period, divided by the funds NAV in February.

Each time series consist of two types of abnormal returns, gross and net. Gross return is simply the raw return from a fund's investment activity. Net return, on the other hand, is adjusted for ongoing expenses as management and administrative fees. Some expenses are not factored in, such as sales charges, which tend to vary from investor to investor.

Independent variables

The variables come from Kenneth French's data library. I am using these risk factors: Mkt-RF, SMB, HML, WML, RMW and CMA, in different combinations depending on which performance model is used. The factors are in the same unit as the abnormal returns, in monthly discrete, and for the same period from 02/2003 – 05/2015.

Statistical Assumptions

Throughout the project statistical models are used to evaluate the performance of active mutual funds. All these statistical models are based on some assumptions

I. **Linearity and additivity**
   No multicollinearity
II. **Statistical independence**
   No autocorrelation
III. **Homoscedasticity**
   Constant variance
IV. **Normality**
   Normally distributed

5. FINDINGS ON FULL SAMPLE

In this section we see a performance evaluation of the full sample of mutual funds, and on different management types with foundation in Cremers and Petajisto's (2009) methodology.

5.1 PRESENTATION

Critics of active management state that active mutual funds take too high fees compared to the abnormal risk adjusted net returns that they deliver. In this matter the alternative index retail funds are more attractive for investors, since they are delivering market returns to lower fees.

TABLE 4 – RISK ADJUSTED NET AND GROSS ABNORMAL RETURNS FOR THE FULL SAMPLE

Fund Type (t-statistics)

Jensen's Alpha	**Carhart Four-Factor Alpha**	**Fama French Five-Factor Alpha**
	Benchmark Adjusted Gross Returns	
Full Sample (4.578***)	Full Sample (5.250***)	Full Sample (3.818***)
	Benchmark Adjusted Net Returns	
Full Sample (0.335)	Full Sample (1.129)	Full Sample (0.070)

Note: P-value < 0.10 * & P-value < 0.05 ** & P-value < 0.01 ***

Source: Own contribution [From appendix C.1, Table (1, 2 and 3)]

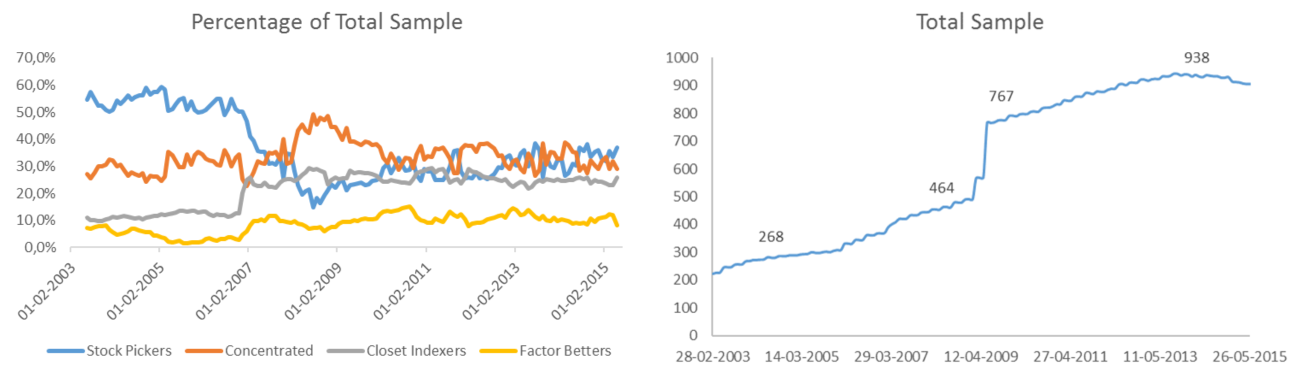
However, Cremers & Petajisto (2009) gave retail investors an option to use AS and TE to pick a certain type of active management that have delivered better risk adjusted abnormal returns than the full sample have.

In the next part the full sample of active funds is sorted into four different types of active management based on AS and TE, and the performance for each type will be analyzed and the results interpreted.

Development of Types of Active Management

In the period from 28/02/2003 to 31/05/2015 the overall number of mutual funds reporting their AS and TE level has increased. In the start of the period the data contain a large concentration of stock pickers, while the other types of active management are small. However, the gap decreases and in general all the management types are well-represented in the sample.

Figure 4 – Time series data of active management types and the full sample



Source: Own Contribution

Markets and management types

This section gives a more detailed picture of the total sample of funds.

Table 5 – Overview of average AS and TE for different markets (Date: 31/05 – 2015)

Country Index	Denmark	Japan	Brazil	Switzerland
AS	53.6	66.6	57.9	36.4
TE	0.115	0.107	0.224	0.05

Regional Index	ACWI Ex USA	Nordic Countries	Europe	AC Asia Pacific Ex Japan
AS	89.1	63.5	71.2	78.4
TE	0.108	0.08	0.09	0.077

Funds with regional benchmark indices have a higher AS in general than country indices based on my selected benchmarks.

5.2 PERFORMANCE EVALUATION

In this section all the active management types are sorted into boxes with Cremers & Petajisto (2009) methodology. Thereafter, all the management types are performance evaluated with foundation in the arithmetic average of the group.

5.2.1 Stock Pickers

This type of active management is trying to create value for their shareholders primarily by selecting stocks based on fundamental analysis. Their bets against the benchmark are not concentrated to specific sectors and thus they are able to hold a well-diversified portfolio with a low TE to their benchmark.

Performance Evaluation

TABLE 6 - RISK ADJUSTED NET AND GROSS ABNORMAL RETURN FOR STOCK PICKERS

Fund Type (t-statistics)

Jensen's Alpha	Carhart Four-Factor Alpha	Fama French Five-Factor Alpha
	Benchmark Adjusted Gross Returns	
Stock Pickers (3.316***)	Stock Pickers (3.819***)	Stock Pickers (2.977***)
	Benchmark Adjusted Net Returns	
Stock Pickers (-0.568)	Stock Pickers (0.076)	Stock Pickers (-0.400)

Note: P-value < 0.10 * & P-value < 0.05 ** & P-value < 0.01 ***

Source: Own Contribution [From Appendix C.1, Table (1.1, 2.1 and 3.1)]

Stock Pickers generate highly significant positive abnormal gross returns. Unfortunately for the investors, all the abnormal returns are eaten by fees which lead to insignificant negative abnormal net returns in two out of three risks adjusted models.

Active share and Tracking Error

TABLE 7 – AVERAGE AS AND TE OF OBSERVATIONS FROM STOCK PICKERS

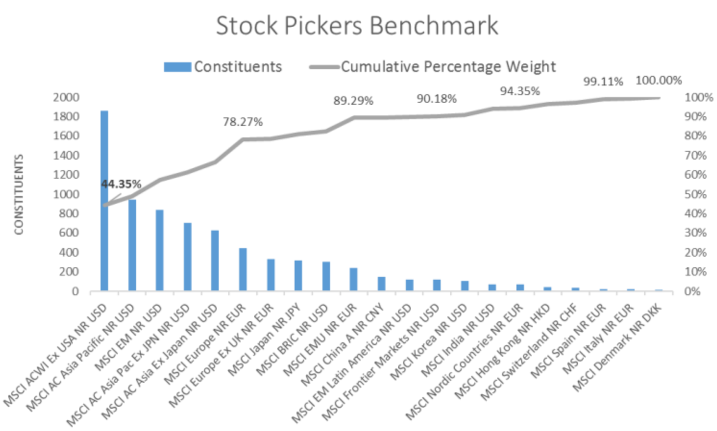
AS	TE
81	0.094

The distribution of the observed AS and TE for the funds in the group are in Appendix A [Figure A.1].

Investment Area

The investment area of this type of active management mostly operates in markets with many constituents.

FIGURE 5 – CUMULATIVE PERCENTAGE OF BENCHMARK FOR STOCK PICKERS (DATE 31/05-2015)



In the graph above there seems to be a tendency that funds classified as Stock Pickers use a benchmark with many constituents. MSCI ACWI Ex USA is used as benchmark for 44.3 percent of the Stock Pickers, while MSCI Italy is only used as benchmark for 0.9 percentages of the Stock Pickers. Setting these numbers in relation to my full sample 314 funds are benchmarked with MSCI ACWI Ex USA and 33 with MSCI Italy. These numbers are when translated into Percentages 33.59 and 3.3 of the full sample, so the MSCI Italy is under weighted as benchmark in the group for Stock Pickers, while MSCI ACWI Ex USA is over weighted in the same group from a full sample perspective.

5.2.2 Concentrated Stock Pickers

This type of active management is both using stock selection and market timing to beat their benchmark. Concentrated Stock Pickers (Hereafter called Concentrated) are taking large concentrated bets in specific sectors against its benchmark and therefore this management type has a high TE to their benchmark.

Performance Evaluation

Table 8 - Risk adjusted net and gross abnormal returns for Concentrated

Fund Type (t-statistics)

Jensen's Alpha	**Carhart Four-Factor Alpha**	**Fama French Five-Factor Alpha**
	Benchmark Adjusted Gross Returns	
Concentrated (4.750***)	Concentrated (5.199***)	Concentrated (4.330***)
	Benchmark Adjusted Net Returns	
Concentrated (2.112**)	Concentrated (2.671***)	Concentrated (2.008**)

Note: P-value < 0.10 * & P-value < 0.05 ** & P-value < 0.01 ***

Source: Own Contribution [From Appendix C.1, Table (1.2, 2.2, 3.2)]

Risk adjusted performance models show that Concentrated is delivering significant abnormal gross returns. Furthermore, this type of management has managed to deliver value for their shareholders after fees. Thus, an average Concentrated mutual fund delivers higher abnormal net returns than an index retail fund manages over this period.

Active share and Tracking Error

Table 9 – Average number of AS and TE for observations on Concentrated

AS	TE
85	0.208

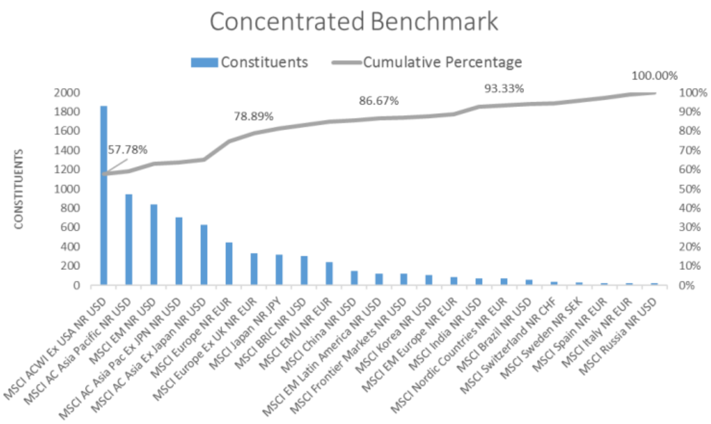
The distribution of the observed AS and TE for the funds in the group is in appendix A [Figure A.2].

Compared to table 8 of Stock Pickers, the average AS values for Concentrated funds is on a higher level. Furthermore, TE is higher, which is obvious, since a high TE is what differentiates Concentrated funds from Stock Pickers.

Investment Area

The investment area of this type of active management is mostly in markets with many constituents.

FIGURE 6 – CUMULATIVE PERCENTAGE OF BENCHMARK FOR CONCENTRATED (DATE 31/05 – 2015)



5.2.3 CLOSET INDEXERS

This type of “active management” is not taking many active bets and not betting on systematic risk factors against the benchmark. Thus, Closet Indexers have both low AS and TE.

Performance Evaluation

TABLE 10 - RISK ADJUSTED NET AND GROSS ABNORMAL RETURNS FOR CLOSET INDEXERS

Fund Type (t-statistics)

Jensen's Alpha	Carhart Four-Factor Alpha	Fama French Five-Factor Alpha
	Benchmark Adjusted Gross Returns	
Closet Indexers (2.652***)	Closet Indexers (3.018***)	Closet Indexers (2.069**)
	Benchmark Adjusted Net Returns	
Closet Indexers (-1.940*)	Closet Indexers (-1.381)	Closet Indexers (-1.975*)

Note: P-value < 0.10 * & P-value < 0.05 ** & P-value < 0.01 ***

Source: Own Contribution [From Appendix C.1, Table (1.3, 2.3 and 3.3)]

The funds which are characterized as Closet Indexers can beat the market in gross returns. However, after fees paid to the management, these funds are underperforming the market with a t-statistic that is significant in a two-sided 90 percent confidence-interval test in two out of three risk adjusted models.

Active Share and Tracking Error

TABLE 11 – AVERAGE NUMBER OF AS AND TE OF OBSERVATIONS FOR CLOSET INDEXERS

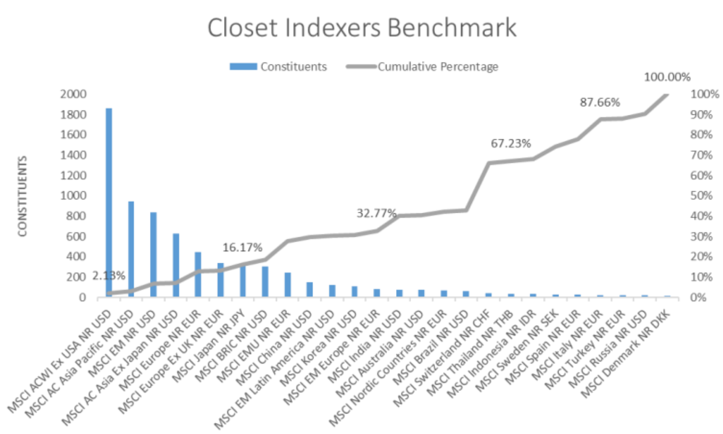
AS	TE
41	0.070

The distribution of the observed AS and TE for the funds in the group is in Appendix A [Figure A.3]

Investment Area

The investment area of this type of active management is mostly in markets with few constituents. MSCI ACWI ex USA only counts for 2.13 % of the funds in this sample. MSCI ACWI ex USA was the most used benchmark for funds in the Stock Picker and Concentrated category with 44.3 and 57.78 %

FIGURE 7 - CUMULATIVE PERCENTAGE OF BENCHMARK FOR CLOSET INDEXERS (DATE 31/05 – 2015)



5.2.4 FACTOR BETTORS

This type of active management is primarily trying to outperform their benchmark by betting on systematic risk factors. They are not taking many active bets, but their bets are concentrated to specific sectors in the benchmark.

TABLE 12 - RISK ADJUSTED NET AND GROSS ABNORMAL RETURNS FOR FACTOR BETTORS

Fund Type (t-statistics)

Jensen's Alpha	Carhart Four-Factor Alpha	Fama French Five-Factor Alpha
	Benchmark Adjusted Gross Returns	
Factor Bettors (2.112**)	Factor Bettors (2.094**)	Factor Bettors (0.950)
	Benchmark Adjusted Net Returns	
Factor Bettors (-0.138)	Factor Bettors (-0.039)	Factor Bettors (-1.050)

Note: P-value < 0.10 * & P-value < 0.05 ** & P-value < 0.01 ***

Source: Own Contribution [From Appendix C.1, Table (1.4, 2.4 and 3.4)]

Active Share and Tracking Error

TABLE 13 AVERAGE NUMBER OF AS AND TE OF OBSERVATIONS FOR FACTOR BETTORS

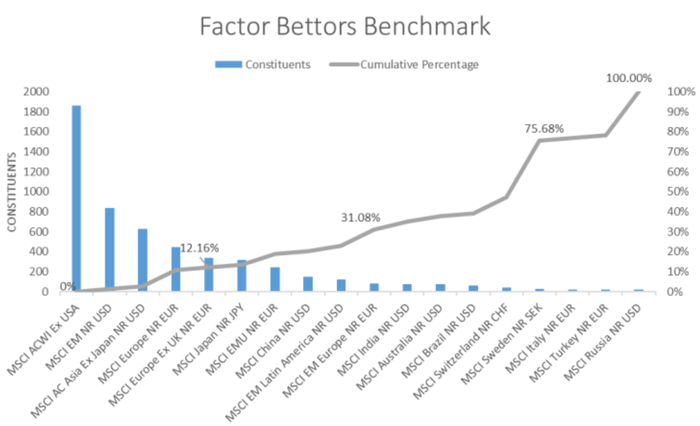
AS	TE
44	0.250

The distribution of the observed AS and TE for the funds in the group are in Appendix A [Figure A.4]

Investment Area

The investment area of this type of active management is mostly in markets with few constituents. 87.84% of the Factor Bettors operated in markets smaller than 335 constituents on 31/05 - 2015, and 24.32% operated in markets smaller than 30 constituents.

FIGURE 8 - CUMULATIVE PERCENTAGE OF BENCHMARK FOR FACTOR BETTORS (DATE 31/05 – 2015)



5.3 CONCLUSION

The data changed a lot from 2003 to 2015 with a total increase of over 400 percent of reported funds in the sample. Figure 4 shows that the ratio of the total sample with low AS funds increased from 2003 to 2015. In the performance evaluation of the full sample, abnormal gross returns in all the three risk adjusted models were positively significant. After adjusted for fees, the significance level dropped and there was no statistical evidence of outperformance in abnormal net returns in the three performance models.

For the different types of active management, the same situation is prevailing for abnormal gross returns. All the management types, except Factor Bettors in one of the performance models, beat their benchmark with a significant t-statistic. However, t-statistics were higher for the types of funds with high AS, Stock Pickers and Concentrated. In net returns, only concentrated funds manage to deliver significant abnormal net returns, at the 95 percent-confidence interval, after adjusted for systematic risk factors. For Closet Indexers, abnormal net returns were negatively significant at the 90 percent-confidence interval (p-value between 0.05 and 0.099) in 2 out of 3 risk adjusted models. Stock Pickers and Factor Bettors both had insignificant abnormal net returns on a high level.

One of the most interesting findings in this section was the relationship between the structure of the funds benchmark and its type of management. The funds that were categorized as Stock Pickers and Concentrated in a much higher degree was benchmarked against indexes with many constituents, while the opposite was the case for Closet Indexers and Factor Bettors.

In the next section I will dig further into their methodology, and the problems that arise when comparing funds from different markets.

6. IMPLICATIONS OF CREMERS AND PETAJISTO

This section provides insight to the problematic definition of AS with the Cremers & Petajisto methodology and shows numerical and analytical examples of how AS and TE is affected by the market in which the fund is domiciled

6.1 ACTIVE MANAGEMENT

AS is an intuitive and easily explainable measure of active management. Furthermore, the term has added a new dimension to the active versus passive debate, since it makes it possible to distinguish between different management styles. However, the investment environment is very complex and many different parameters affect the outcomes. Cesari & Panetta (2002) argues that a sample needs to be homogenous for giving valid results.

Cremers & Petajisto (2009) only performance evaluates US stocks with US benchmarks from Russell, S&P and Wilshire. All these benchmarks have a high number of constituents, so they are comparable. However, in the rest of the world there are some very small benchmarks. For example, MSCI Denmark has 16 constituents, MSCI Italy has 24 and MSCI Spain has 25.

The environment between a fund operating in a market with 1000 different stocks and a fund operating in a market with only 20 or 30 different stocks is very different. Furthermore, some markets are harder to operate in since the average correlation between the assets in the market is very high and this affects the opportunity to use asset allocation to increase risk adjusted returns.

The effect index constituents has on AS makes larger performance evaluation on funds with many different investment areas biased, since funds investing in larger markets have naturally a higher level of AS than funds investing in smaller markets. This is problematic since there is no evidence that larger markets increase risk adjusted returns of funds. Thus, the size of the funds benchmark should not have a significant influence on AS which is used in the methodology.

Cremers & Petajisto (2009) define the difference between a Stock Picker and a Closet Indexer in terms of AS being on the limit of 60 percent. Funds with a higher than 60 percent AS are Stock Pickers, while funds with lower AS are Closet Indexers. In Cremers & Petajisto study, Stock Pickers outperformed Closet Indexers, so AS has been used as a proxy for performance. High AS funds are better performers than Low AS funds

6.2 SIZE AND AS

This section is based on Monte Carlo simulations to find the effect of the portfolio size and numbers of constituents that an index has on a fund's level of AS.

The objective is to become more aware of how AS is affected by market characteristics and, thus, can develop a sharper conclusion based on the whole picture instead of only the funds AS level.

Model assumption

The Monte Carlo model will build on these assumptions:

- The benchmark index is equally weighted
- The fund is minimum investing in 10 stocks
- The fund is not allowed to short stocks
- The fund is not able to invest outside the benchmark.

Objective function of Monte Carlo simulation is

$$Active\ Share = \frac{1}{2}\sum_{i=1}^{N}|\omega_{fund,i} - \omega_{benchmark,i}| \tag{17}$$

Each stock in the benchmark is equally weighted

$\omega_{benchmark,i} = \frac{1}{N}$, were N is constituents in the index.

I have randomized the weights of the active funds' investments in the index with a randomized uniform variable between [0,1]

$$X \sim U[0,1] \tag{18}$$

To replicate the investment into the index, I divide the sequence of IIID random uniform variables, $X_1, X_2, \dots, X_n$, by the total sum to reach investments weights that in total gives 1.

$$\omega_{fund,i} = \frac{X_i}{\sum_{i=1}^{n} X_i} \tag{19}$$

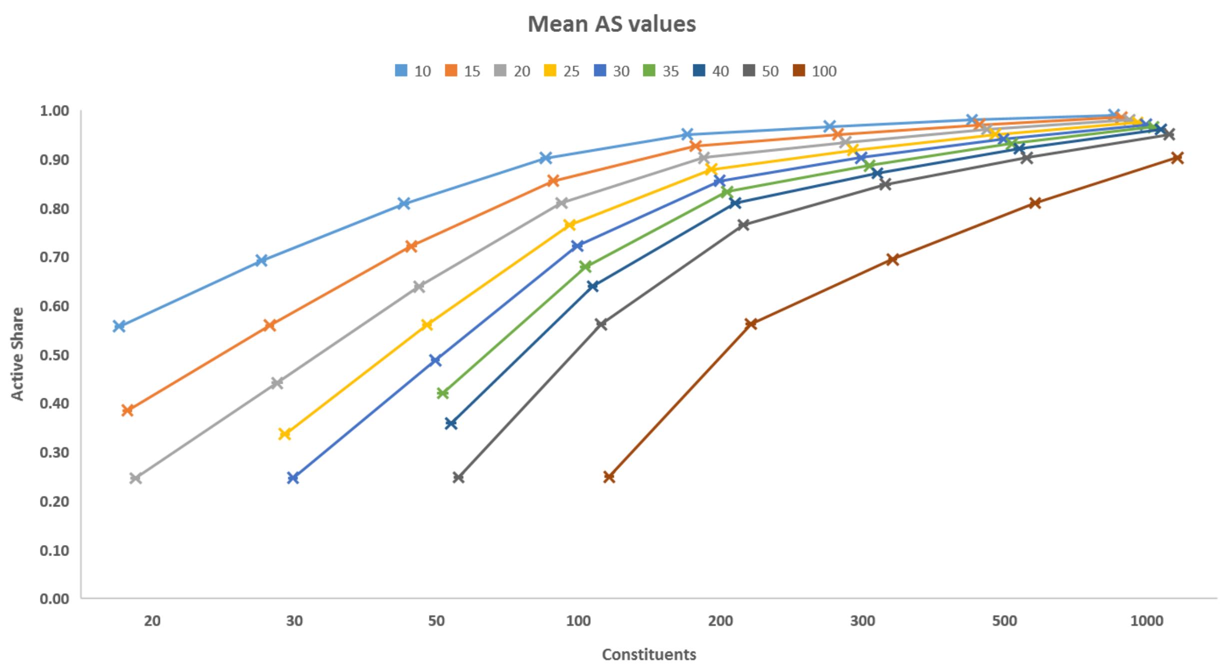
To get a good estimation of how AS is affected by constituents, the simulation of the funds different investments weights in the index is repeated 10.000 times.

Findings

Through the Monte Carlo model, I have reached some interesting findings on how AS behave when changing the funds stock portfolio and the size of the benchmark.

Most important of all the findings is that AS is affected by these two variables. The correlation between AS and the size of the stock portfolio is negative correlated, while AS is positively correlated to the size of the funds benchmark.

FIGURE 9 – MEAN SIMULATED AS VALUES FOR 9 FUNDS WITH DIFFERENT NUMBER OF STOCKS IN THEIR PORTFOLIO ON AN INCREASE IN CONSTITUENTS OF THE BENCHMARK



Source: Own Contribution

$$\text{Mean AS} = \frac{\sum_{i=1}^{N} Fund_{AS,i}}{N} \tag{20}$$

TABLE 14 - MEAN VALUES OF ACTIVE SHARE FOR EVERY FUND IN THE SIMULATION

	Constintuents							
Stock Portfolio	**20**	**30**	**50**	**100**	**200**	**300**	**500**	**1000**
	Average Active Share							
10	0.558	0.692	0.809	0.902	0.951	0.967	0.980	0.990
15	0.385	0.559	0.721	0.855	0.926	0.951	0.970	0.985
20	0.246	0.442	0.639	0.810	0.902	0.934	0.960	0.980
25		0.337	0.561	0.765	0.879	0.918	0.951	0.975
30		0.247	0.488	0.722	0.855	0.902	0.941	0.970
35			0.420	0.680	0.832	0.887	0.931	0.965
40			0.359	0.639	0.810	0.871	0.922	0.960
50			0.248	0.562	0.765	0.848	0.902	0.951
100				0.249	0.562	0.694	0.810	0.902

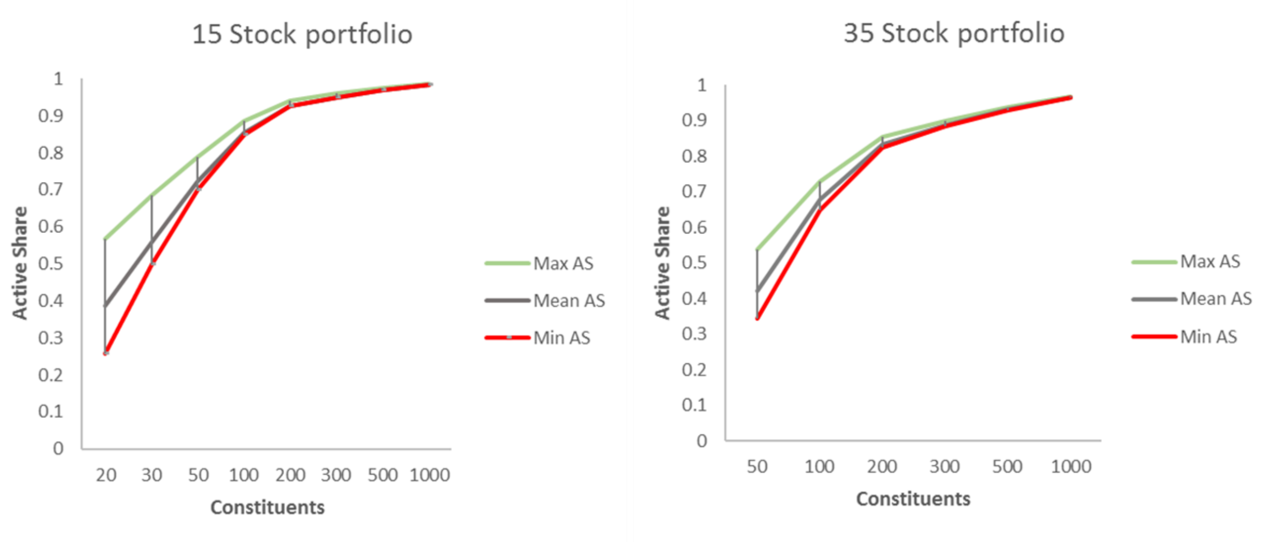
Source: Own contribution

Fund A and Fund B have the same benchmark with 500 constituents. The only difference is that Fund A has a stock portfolio with 40 stocks, while Fund B only has 15 stocks. In the light of MC Simulation comparing those funds will be problematic since Fund A has a natural AS of 92.16 percent, while Fund B has a natural level of 97.02 percent.

Since Cremers and Petajisto methodology is affected by a fund's environment, it seems illogical to use AS to decompose active management into different groups. Some funds operate in an environment with a natural high level of AS, while other funds are operating in low natural level of AS. However, most active mutual funds operate in large markets, and the effect Stock Portfolio and constituent size has on AS when the benchmark is large is marginally small.

Marginal effect from stock portfolio and constituents size on AS is highest for funds using small benchmark indices. In my sample, I use funds with large benchmark and funds with small benchmark and this is critical for my methodology. Including both types of funds in a whole sample would result in funds with smaller benchmark becoming Closet Indexers and Factor Bettors, while funds with larger benchmark are Stock Pickers and Concentrated.

FIGURE 10 – ACTIVE SHARE INTERVAL ON SIZE OF CONSTITUENTS FOR TWO DIFFERENT FUNDS WITH 10.000 MONTE CARLO SIMULATIONS



Source: Own Contribution

TABLE 15 – ACTIVE SHARE NUMBERS FOR FIGURE 10

	Constintuents							
	20	30	50	100	200	300	500	1000
15 stocks								
Max AS	0.567	0.684	0.788	0.887	0.942	0.960	0.975	0.987
Mean AS	0.385	0.559	0.721	0.855	0.926	0.951	0.970	0.985
Min AS	0.256	0.500	0.700	0.850	0.925	0.950	0.970	0.985
35 stocks								
Max AS			0.539	0.728	0.856	0.901	0.940	0.969
Mean AS			0.420	0.680	0.832	0.887	0.931	0.965
Min AS			0.345	0.650	0.825	0.883	0.930	0.965

Source: Own Contribution

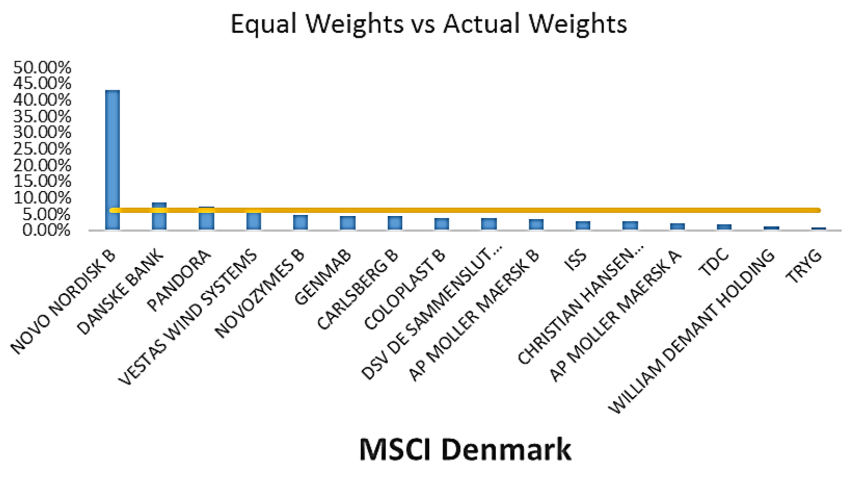
From a theoretical point of view AS should only be used to compare funds with the same benchmark and same size of stock portfolio using relative quantiles of AS and TE to sort the funds. However, finding a statistical valid sample size with these criteria is problematic. Consequently, there needs to be a balance between benchmark homogeneity of the funds and the statistical power of the sample.

In Cremers & Petajisto (2009) all the funds in the sample have large benchmarks and thus the methodology is not affected by causality between constituents, stock portfolio size and AS. However, using their methodology on the rest of the world will, from a theoretical point of view, not make sense because the gap between the smallest benchmark and largest benchmark is very wide.

Discussion of Assumptions

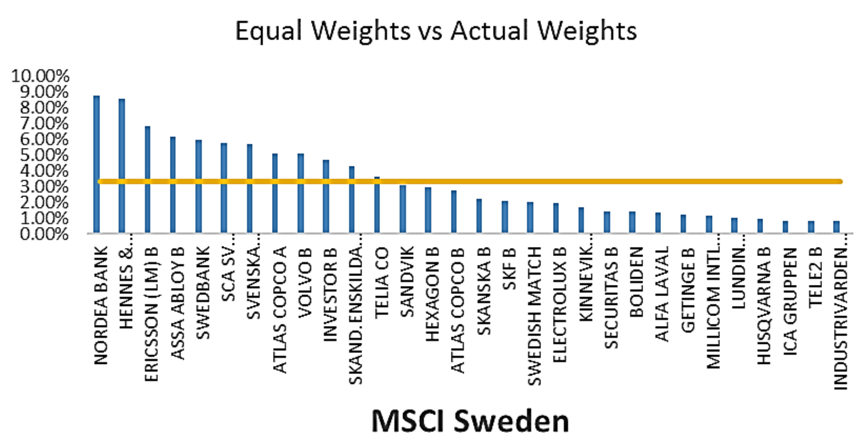
1. Assumption - *The benchmark index is equally weighted*

FIGURE 11 – MSCI DENMARK



Source: Own Contribution [From appendix]

FIGURE 12 – MSCI SWEDEN



Source: Own Contribution [From appendix]

The empirical data on the actual weights of the equity indexes shows that index constituents vary in weight. Especially in the Danish equity index there is a wide gap between the highest weighted constituent and the lowest. Novo Nordisk is weighted with 43.02 percent of the total, while TRYG is only weighted with 0.93 percent of the total index. MSCI Sweden consists of more equally weighted constituents, but still there is a large difference between the weight of the highest and lowest constituent. Nordea Bank is weighted with 8.76 percent, while Industrivarden C is weighted with 0.82 percent as the lowest weighted equity in the index.

From an empirical point of view this assumption is not realistic. However, in a Monte Carlo setting the assumption is meaningful, since it simplifies the objective and gets realistic results. An alternative setting to equally weighted indices is to randomize the indices' weights for each constituent and set the fund's portfolio to equal weight. However, from an investment point of view active managers should take positions, while the index should only reflect the market. Thus, a passive, equally weighted index, and a portfolio manager actively taking different randomized positions in constituents of the index reflect the reality.

2. Assumption - *The fund is minimum investing in 10 stocks*

This assumption was made, because there are very few mutual funds with a portfolio of less than 10 stocks. An investor is normally investing into a mutual fund with the objective of diversification, and a fund with less than 10 stocks is not fully diversified. Thus, funds with less than 10 stocks were delimited from the model.

3. Assumption - *The fund is not allowed to short stocks*

This assumption is made for simplistic reason, but seems reasonable since most open-ended mutual funds have restriction on short selling stocks.

4. Assumption - *The fund is not able to invest outside the benchmark*

This ensures funds investing in their assigned benchmark. Otherwise, funds would have the option to invest outside their benchmark and skew AS upwards.

Conclusion

Cremers and Petajisto (2009) methodology has some weakness, since AS is affected by other variables in form of portfolio size and constituent. However, AS is only affected in a significant way in smaller markets which makes it a good tool to evaluate funds in larger markets.

In my performance studies I have included both small markets and large markets, which makes the evaluation complicated since market characteristics of the funds will have a high influence on the decomposition into the different categories of active management. However, I will try to adapt my performance evaluation to these findings and sort my funds into large markets and small markets, to minimize the effect of portfolio size and constituents on my findings. In the next section I will test how a fund's benchmark effects a fund's TE.

6.3 ASSET CORRELATION AND TRACKING ERROR

Another parameter in the Cremers and Petajisto (2009) methodology is TE. In this section the expression of TE is deducted with formulas from modern portfolio theory to show evidence of a negative correlation between the average cross correlation in the market and the level of tracking error on the mutual funds return. Tracking error is basically the standard deviation of the funds return to its benchmark.

The idea came to me by thinking about two extreme cases – a market which is perfectly correlated and a market with no correlation at all. On the perfectly correlated market a mutual fund would deviate from the benchmark index by holding a higher or lower weight in risky or safe assets, but the assets will always move in the same direction and thus have a natural low tracking error. In contrast, a market with zero asset correlation, the benchmark index and the funds can move in opposite direction, which increase the spread of the returns - TE. Consequently, funds operating in markets with low cross correlation should have a higher natural level of TE than funds operating in markets with high average cross correlation.

These findings will be tested through deduction of the formula of tracking error to find evidence whether or not there is a negative relationship between Cross Correlation and TE for the funds on the market.

Assumptions:

- The mutual fund is restricted to only invest in stocks from the index
- Mutual fund deselecting stocks is a short position
- Cross correlation is the same across all positions

The mutual funds and the index weights and returns of the portfolio

$$R_{Fund} = \sum_{i=1}^{n} \omega_{F,i}, R_i \tag{21}$$

$$R_{Index} = \sum_{i=1}^{n} \omega_{I,i}, R_i \tag{22}$$

n is the number of constituents in the MSCI index

Tracking Error:

$$TE = Std.Dev(\sum_{t=1}^{T}\sum_{i=1}^{n}(\omega_{F,i} - \omega_{I,i}) * R_{i,t}) \tag{23}$$

$$TE^2 = Var(\sum_{t=1}^{T}\sum_{i=1}^{n}(\omega_{F,i} - \omega_{I,i}) * R_{i,t}) \tag{24}$$

$$Set\ \Delta_i = \omega_{F,i} - \omega_{I,i}$$

The sensitivity of TE wrt ρ is:

$$\frac{\delta TE}{\delta \rho} = \sqrt{T} * \frac{1}{2}(\sum_{i=1}^{n}\Delta_i^2\sigma_i^2 + \rho\sum_{i=1}^{n}\sum_{\substack{j=1 \\ j\neq i}}^{n}\Delta_i\Delta_j\sigma_i\sigma_j)^{-\frac{1}{2}} * \sum_{i=1}^{n}\sum_{\substack{j=1 \\ j\neq i}}^{n}\Delta_i\Delta_j\sigma_i\sigma_j \tag{25}$$

$$\frac{\delta TE}{\delta \rho} = \frac{1}{2} * \frac{T}{TE}\sum_{i=1}^{n}\sum_{\substack{j=1 \\ j\neq i}}^{n}\Delta_i\Delta_j\sigma_i\sigma_j \tag{26}$$

[Full overview of mathematical derivation in Appendix E]

The mathematical derivation of TE is not enough to conclude a relationship between average cross correlation and TE. However, correlation is a good measure to use for market characteristics, since correlation is one of the groundwork components in modern portfolio theory. Intuitively a relationship between TE and correlation in the market makes sense, and all these points taken into consideration markets are sorted after it.

7. MARKET CLASSIFICATION

In this section a description of the classification methodology, that is used to sort the funds into different market types based on their benchmark, will be provided. Thereafter, the funds' performance is evaluated with the Cremers & Petajisto (2009) approach.

7.1 SORTING INVESTMENT MARKETS

The benchmark of the different funds is sorted after size and average correlation. This approach should guarantee that the funds are comparable in terms of AS and TE, since AS and TE are affected by the funds market characteristics in terms of correlation and number of constituents in its benchmark.

In the sample are funds with investment areas from all around the world. Some are investing in developed markets as Denmark, Sweden and Spain, some in emerging markets as India, Brazil and China and others in regional indexes consisting of both developed and emerging markets [3].

Many of the funds in the sample are European and operate in developed markets. For giving a more informative analysis of the sample, funds attached to developed European markets have been decomposed into an isolated sample. The argument for isolating the European developed countries (Hereby referred to as European markets) is that Kenneth French calibrates his factor models based on different regions, where one of the factors is a Global excluding USA (Hereby referred to as Global Markets) that fit well to my sample in general. However, with a high concentration of European developed countries in the sample it would not be representative of Global markets. Thus, European markets are isolated from the sample and I am using a European calibrated factor models on them.

7.1.1 SIZE

In the previous section it became clear that the funds natural level of AS is positive correlated with the size of the market it operates in. Consequently, funds should be sorted in agreement of their operation in large markets or small markets.

The size of the market is assessed through the MSCI webpage on index constituents [3], and the limit used to distinguish between small and large market funds is set with the median of constituents in the benchmarks for the sample. Using the median as the distinction limit gives two equally weighted groups in terms of benchmark with small and large market funds.

7.1.2 CORRELATION

Mutual funds, in general, use a diversified investment strategy on a market by allocating assets with the covariance matrix to optimize returns to a given standard deviation. In the whole investment process cross correlation between assets is an important parameter in modeling return and standard deviation with portfolio theory. Thus the average level of cross correlation between the assets in the fund's investment area is critical for the effect of using asset allocation. Furthermore, there appears to be mathematical evidence indicating that funds that operate in a market with high average cross correlation have a lower natural level of TE. Thus, funds are decomposed after their benchmarks into high and low average cross correlation markets.

After the decomposition, there are four different market classifications: Large Market with High Correlation, Large Market with Low Correlation, Small Market with High Correlation and Small Market with Low Correlation.

7.2 DATA AND METHODOLOGY

My approach for finding the average market correlations is to perform a cross correlation of all the stocks in the market index, and then finding the average cross correlation. However, many of the benchmark indices consist of many constituents and for them a random sample of 50 stocks from the index is used to estimate the average correlation. I am aware that the weights of the stocks in the index variate much, but I will not take weights into consideration since mutual funds have no asset allocation restriction on weights.

My random generator is based on excels random number generation through a VBA sub, where I am using a uniform distribution to pick the stocks.

$$\boldsymbol{X} \sim \boldsymbol{U}[\mathbf{1}, \boldsymbol{N}] \tag{27}$$

N is the number of constituents in the index.

$$\boldsymbol{Average\ \rho(X_i, Y_j)} = \frac{\frac{\mathbf{1}}{\boldsymbol{N-1}} * \sum_{\substack{t=1 \\ j \neq i}}^{N} \left(\boldsymbol{X_{it}} - \overline{\boldsymbol{X_i}}\right) * \left(\boldsymbol{Y_{jt}} - \overline{\boldsymbol{Y}}_{\boldsymbol{i}}\right)}{\sqrt{\frac{\mathbf{1}}{\boldsymbol{N-1}} \sum_{t=1}^{N} \left(\boldsymbol{X_{it}} - \overline{\boldsymbol{X_i}}\right)^{\mathbf{2}}} * \sqrt{\frac{\mathbf{1}}{\boldsymbol{N-1}} \sum_{t=1}^{N} \left(\boldsymbol{Y_{it}} - \overline{\boldsymbol{Y_i}}\right)^{\mathbf{2}}}} \tag{28}$$

The error term is IID from t=1 to N

The constituents are found through MSCI webpage, where they report all the constituents in their indices [2]. By picking 50 random stocks for the larger indices, I get 1225 different cross correlations, which is expected to be a good estimate for the overall cross correlation in the index. The reasoning for doing a randomly picked sample is that I am downloading all the stocks in the index manually, and since it is problematic to download 1847 (MSCI ACWI Ex USA) different stocks, I am basing the average cross correlation from the larger indexes on statistical robust estimates. The limit between using a random sample and using the whole index is set to 80 constituents.

The returns used for finding the average cross correlation in the index are monthly and found through Datastream, where I have used a total return index for the stock, since it takes dividends into account:

$$\text{Total return index (RI)} = \frac{(P_t - P_{t-1}) + D_t}{P_{t-1}} \tag{29}$$

P_t = Price today, P_{t-1} = Price last month, D_t = Dividends reinvested in the period.

The data coverage has been set to the period (2003-2015), same as my performance evaluation of the funds.

There have been some challenges in the estimation of the average cross correlation, which have made it necessary to make some exclusions on the raw data. Some of the constituents in the index has not reported Total return (RI) on monthly basis and thus there are several zero returns over the period. Consequently, stocks consisting of zero returns in three or more following months have been excluded as a sign of bad coverage of the stock by Thomson Reuters.

Another challenge has been that some of the constituents in the index have only recently been listed and thus there are only a few observations available of the total shareholder return of the stock. Since cross correlation of a stock with so few observations is not statistically reliable – a minimum limit of available returns for a stock has been set to 36 (3 years). The last challenge has been that some of the indices consist of different types of the same stock[21], which is almost perfectly correlated and thus are basically the same stock. In the case of an index consisting of different types of the same stock, I have decided to exclude the type with the lowest weight in the index.

7.2.1 Data Coverage

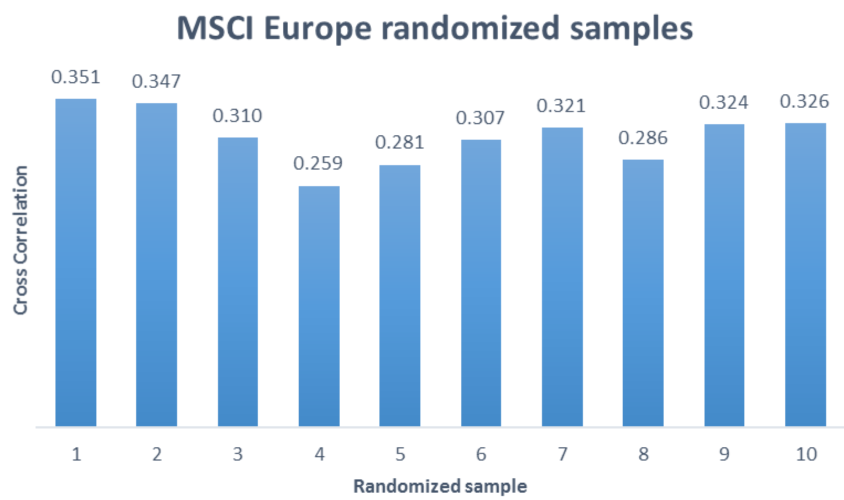
The data coverage for finding average cross correlations has been on a high level for most markets even when excluding stocks based on my selection criteria's. However, as the constituents of the market increase, my decision on using a randomized sample to represent the average overall correlation set in, and the coverage of larger markets is on a much lower level than for the smaller markets[22]. In the next section, the estimate for average correlation on MSCI Europe is tested to guarantee that the estimate found from random sampling 50 stocks on a large market is representative for the overall correlation.

[21] Example: AP Møller Maersk B and AP Møller Maersk A are both in the MSCI Denmark.
[22] Appendix 3

7.2.2 Testing the Estimate

The following graph shows the estimate for average correlation based on ten different randomized samples with 50 stocks in each from the MSCI Europe index with 447 constituents. After excluding stocks that did not fulfill the selection criteria there were 416 stocks left in the index.

Figure 13 – Ten different estimates for cross correlation of the MSCI Europe from a generated random sample from the index.



Source: Own Contribution [From time series returns on constituents of MSCI Europe]

Even if there is variation in the average cross correlation between the assets for the ten different randomized samples, the estimates for the different samples are fairly close, and this should give enough statistical power to find the markets with high correlation and low correlation. The full sample average correlation for MSCI Europe is 0.3131, so the estimate gives a fairly accurate value of the average cross correlation for the index.

7.3 MARKET CLASSIFICATION AND PERFORMANCE MODEL

In the previous section a relationship between active share and market size was found. Consequently, a fund's natural level of AS is affected by the market situation of the fund. In this section our active share methodology is still the same, but based on previous findings a further decomposition of investment areas was necessary.

The reason for making this further decomposition is that otherwise my conclusion would basically be based on how funds operating in large markets have performed against funds operating in small markets. Funds in large markets are overrepresented in the Stock Picker and Concentrated category, while underrepresented in the Closet Indexer and Factor Bettor category.

My four decompositions are based on funds with investment areas in Large Markets with High Asset Correlation, Large Markets with Low Asset Correlation, Small Markets with High Asset Correlation, and Small Markets with Low Asset Correlation.

Sorting Markets	Median
Constituents in Benchmark	79
Large Market Average Cross Correlation	0.254
Small Market Average Cross Correlation	0.369

TABLE 16 – OVERVIEW OF MARKET CLASSIFICATION FOR THE BENCHMARKS

Large Market High Correlation	Large Market Low Correlation	Small Market High Correlation	Small Market Low Correlation
EUROPE	**EUROPE**	**EUROPE**	**EUROPE**
EMU	None benchmark	Italy	Denmark
EM Europe	**GLOBAL**	Spain	Nordic Countries
Europe Ex UK	EM Latin America	Sweden	Switzerland
Europe	BRIC	**GLOBAL**	**GLOBAL**
GLOBAL	AC Asia Pacific Ex Japan	Poland	Australia
China	AC Asia Ex Japan	Russia	Brazil
Japan	EM	Thailand	India
Korea	AC Asia Pacific	Turkey	Indonesia
	Frontier Markets		Hong Kong

Source: Own Contribution from Appendix B [Table 3.B]

7.4 PERFORMANCE EVALUATION OF MARKETS

All the funds in the different markets will now be performance evaluated with three different risk adjusted models: Jensen's alpha, Carhart four-factor and Fama French five-factor. I am aware of the Joint hypothesis problem[23], but my abnormal returns will be based on findings from these models.

7.4.1 LARGE MARKET WITH HIGH CORRELATION

This market classification has funds with high natural level of AS and a low natural TE. In this sample are funds with investment area in Europe and Global. Funds in this classification are mostly benchmarked to regional indices, but some are also benchmarked to country indices with many constituents.

With the Jensen's alpha model only European Stock Pickers generates significant positive abnormal gross return with t-statistics of 2.625. European Stock Pickers lose their significant abnormal return after returns are adjusted for fees, and only generate abnormal net returns with t-statistics of -0.132. The most

[23] True risk-adjusted abnormal returns cannot be tested, because there will always be a question if the factors reflect the underlying risk.

interesting result for net returns is that European Closet Indexers delivers highly significant negative net abnormal returns.

Extending the risk adjusted model to Carhart's Four-Factor model does not affect the findings in term of significance[24]. However, the t-statistics for European Stock Picker and Global Concentrated funds changes to 3.211 and 2.229 for abnormal gross returns, but after adjusted for fees the funds get insignificant t-stats of 0.508 and 0.969. For European Closet Indexers' the t-statistic for their negative abnormal net returns is still highly significant.

Fama French Five-Factor models reaches the same conclusions as the two others models. European Stock Pickers and Global Concentrated funds generate higher positive abnormal gross returns than the market, but since their charging fees for their operational expenses in buying information, the abnormal net returns left for the retail investor are insignificant. For the European Closet Indexers, the funds were not even able to generate significant abnormal gross returns before fees and this lead to highly significant negative net abnormal returns for the funds, which means there is statistical evidence that shows that retail investors are losing money by investing in funds that are characterized as European Closet Indexers, which operates in Large Markets with High Correlation.

TABLE 17 - KEY FINDINGS FOR LARGE MARKETS WITH HIGH AVERAGE ASSET CORRELATION

Large Market High Correlation
Fund Type (t-statistics)

Jensen's Alpha	**Carhart Four-Factor Alpha**	**Fama French Five-Factor Alpha**
	Benchmark Adjusted Gross Returns	
European Stock Pickers (2.625***) Global Concentrated (1.851*)	European Stock Pickers (3.211***) Global Concentrated (2.229**)	European Stock Pickers (1.800*) Global Concentrated (2.011**)
	Benchmark Adjusted Net Returns	
European Closet Indexers (-4.731***)	European Closet Indexers (-4.158***)	European Closet Indexers (-4.251***)

Note: P-value < 0.10 * & P-value < 0.05 ** & P-value < 0.01 ***

Source: Own Contribution [From Appendix C.2]

7.4.2 LARGE MARKET WITH LOW CORRELATION

This market classification consists of funds with a high natural level of AS and TE. In this sample funds are only attached to the global market. Furthermore, the sample only consists of funds benchmarked to regional indices.

[24] Same funds are still significant by using the two-sided 95 percent confidence level (-1.96, 1.96)

With foundation in the Jensen's alpha no funds generate significant abnormal gross returns. After fees, management types with low AS, Closet Indexers and Factor Bettors, deliver significant negative abnormal net returns with t-stat of -5.252[25] and -2.321.

Extending the risk factors with SMB, HML and WML changes the findings. Concentrated funds are now able to generate highly significant positive abnormal gross returns with a t-stat of 4.212, even after adjustment for fees, Concentrated still manage to generate abnormal returns with t-stat of 2.339. The findings on Closet Indexers and Factor Bettors have not changed, the groups still deliver significant negative abnormal net returns with t-stats of -4.498 and -2.431.

The performance model with the Fama French's five-factors reaches the same conclusion as Carhart's four-factors. Retail investors can increase their expected wealth by investing into a Concentrated fund on a large market with low correlation. Conversely, investments into funds with low level of AS (Closet Indexers and Factor Bettors) destroy expected value for retail investors.

TABLE 18 - KEY FINDINGS FOR LARGE MARKETS WITH LOW AVERAGE ASSET CORRELATION

Large Market Low Correlation
Fund Type (t-statistics)

Jensen's Alpha	Carhart Four-Factor Alpha	Fama French Five-Factor Alpha
	Benchmark Adjusted Gross Returns	
	Global Stock Pickers (1.835*)	Global Stock Pickers (1.808*)
	Global Concentrated (4.212***)	Global Concentrated (4.153***)
	Benchmark Adjusted Net Returns	
Global Closet Indexers (-5.252***)	Global Concentrated (2.389**)	Global Concentrated (2.446**)
Global Factor Bettors (-2.321**)	Global Closet Indexers (-4.498***)	Global Closet Indexers (-4.482***)
	Global Factor Bettors (-2.431**)	Global Factor Bettors (-2.098**)

Note: P-value < 0.10 * & P-value < 0.05 ** & P-value < 0.01 ***

Source: Own Contribution [From Appendix C.3]

7.4.3 SMALL MARKET WITH HIGH CORRELATION

This market classification has funds with low natural level of AS and low natural TE. In this sample are both European and Global funds. Funds in this market classification are only benchmarked to country indices.

In the Jensen's alpha regression on gross returns all types of active management in Europe are creating abnormal returns. For global funds Concentrated and Factor Bettors deliver abnormal returns. After

[25] P value is lower than 0.01

adjusted for fees, none of the management types could deliver significant abnormal net returns to the retail investors.

With Carhart's four-factor performance model all management types of European funds are delivering significant positive abnormal returns with t-stat between 2.217 and 2.851. For Global funds, only Factor Bettors delivers positive abnormal gross returns. After fees, none of the groups of funds in the market delivered significant abnormal net returns, but Concentrated delivered significant abnormal returns based on a 90-confidence interval.

Fama French Five-Factor model reaches different results. For European markets, only Factor Bettors delivered significant positive abnormal gross returns, which is a bit different than expected. After fees, none of the management types delivered significant risk adjusted abnormal net returns.

TABLE 19 - KEY FINDINGS FOR SMALL MARKETS WITH HIGH AVERAGE ASSET CORRELATION

Small Market High Correlation
Fund Type (t-statistics)

Jensen's Alpha	Carhart Four-Factor Alpha	Fama French Five-Factor Alpha
	Benchmark Adjusted Gross Returns	
European Stock Pickers (2.142**)	European Stock Pickers (2.127**)	European Factor Bettors (2.255**)
European Concentrated (2.659***)	European Concentrated (2.851***)	
European Closet Indexers (2.146**)	European Closet Indexers (2.471**)	
European Factor Bettors (2.001**)	European Factor Bettors (2.295**)	
Global Concentrated (2.016**)	Global Concentrated (1.784*)	
Global Factor Bettors (2.173**)	Global Factor Bettors (2.037**)	
	Benchmark Adjusted Net Returns	
	Europe Concentrated (1.712*)	

Note: P-value < 0.10 * & P-value < 0.05 ** & P-value < 0.01 ***

Source: Own Contribution [From Appendix C.4]

7.4.4 SMALL MARKET WITH LOW CORRELATION

This market classification has funds with low natural level of AS and high natural TE. The sample includes both European and Global funds. Most of them are benchmarked to country indices, but there is also a regional benchmark.

From Jensen's alpha model Concentrated and Closet Indexers have significant positive abnormal gross returns for European markets. In Global markets, only Stock Pickers had significant abnormal gross return in the evaluated period. Unfortunately for the retail investors a large part of the abnormal gross return in these groups are collected by the management in terms of fees, which results in none of the management types delivering significant positive net abnormal returns for the retail investor.

With Carhart's four-factors the findings are still the same. For European markets Concentrated and Closet Indexers are delivering significant positive abnormal gross returns. In the other category, Global market, Stock Pickers, Concentrated and Closet Indexers deliver significant positive abnormal gross returns. The most interesting result is that Closet Indexers in global markets delivered abnormal returns with a t-stat of 3.145[26]. After adjusted for fees, none of the groups of active managements delivered significant abnormal net returns.

From the lenses of Fama French's five-factors none of the groups in the European market performed significant abnormal gross returns. In the Global market, Stock Pickers, Concentrated and Closet Indexers were all able to deliver significant positive abnormal gross returns; Closet Indexers had the highest t-stat (3.371). After fees, none of the management types were able to deliver significant abnormal net returns.

TABLE 20 - KEY FINDINGS FOR SMALL MARKETS WITH LOW AVERAGE ASSET CORRELATION

Small Market Low Correlation

Fund Type (t-statistics)

Jensen's Alpha	**Carhart Four-Factor Alpha**	**Fama French Five-Factor Alpha**
	Benchmark Adjusted Gross Returns	
European Concentrated (2.036**)	European Concentrated (2.167**)	Global Stock Pickers (2.559**)
European Closet Indexers (2.362**)	European Closet Indexers (2.248**)	Global Concentrated (2.150**)
Global Stock Pickers (2.617***)	Global Stock Pickers (2.674***)	Global Closet Indexers (3.378***)
Global Concentrated (2.226**)	Global Concentrated (2.433**)	
Global Closet Indexers (2.403**)	Global Closet Indexers (3.145***)	
	Benchmark Adjusted Net Returns	

Note: P-value < 0.10 * & P-value < 0.05 ** & P-value < 0.01 ***

Source: Own Contribution [From Appendix C.5]

[26] P-value lower than 0.01

7.4.5 Overview of Performance Evaluation

Table 21 – Key findings with the Fama French Five Factor Model on all markets

Fund type (t-statistics)

Large Market High Correlation	Large Market Low Correlation	Small Market High Correlation	Small Market Low Correlation
	Fama French Five-Factor Alpha on Gross Returns		
Global Concentrated (2.011**)	Global Concentrated (4.153***)	European Closet Indexers (2.471**)	Global Stock Pickers (2.559**)
		European Factor Bettors (2.255**)	Global Concentrated (2.433**)
		Global Factor Bettors (2.037**)	Global Closet Indexers (3.378***)
	Fama French Five-Factor Alpha on Net Returns		
European Closet Indexers (-4.251***)	Global Concentrated (2.446**)		
	Global Closet Indexers (-4.482***)		
	Global Factor Bettors (-2.098**)		

Notes P-value < 0.05 ** & P-value < 0.01 ***

Source: Own Contribution [From Appendix C. [2-5]

In gross returns there are 4 out of 8 models with significant abnormal return funds from the groups with a high level of AS - Stock Pickers or Concentrated funds. There is a difference in the performance of the groups in the large market and the small market.

On the larger markets only Concentrated funds are outperforming, while on the smaller markets Stock Pickers, Closet Indexers and Factor Betters are delivering significant abnormal returns. On both the Small market with high and low correlation Closet Indexers are delivering the highest t-statistics for risk adjusted abnormal gross returns.

In net returns there are only models from the larger markets that get significant alphas. European Closet Indexers are not able to justify for their fees in this market and are delivering a highly negative alpha with t-statistics of -4.251. In the Large Market with Low Correlation Concentrated funds, on the other hand, are able to justify for their higher operational cost by delivering positive alpha for the shareholders after adjusted for fees and systematic factor risks. On the same market, Global Closet Indexers and Global Factor Bettors are underperforming the market, so that the difference between the different types of active management has been high on this market.

7.4.6 Hypothesis Testing Between Stock Pickers and Closet Indexers

In this section one sided hypothesis are tested since Cremers and Petajisto (2009) concluded that funds with high AS outperforms funds with low AS. Thus, hypotheses are tested on that Stock Pickers outperforms Closet Indexers in average net returns for all the markets and both for European and Global regions.

1. Tested sample is larger than n>30
2. Normally distributed errors term

Approach

One sided hypothesis test is performed on two normal distributions with different variances and number of observations. The confidence interval of the test is 95 percent and thus, Z-values lower than 1.65 is accepted, while a Z value higher than 1.65 will be rejected.

An accepted hypothesis means that there is no statistical evidence that Stock Pickers are outperforming Closet Indexers, while the opposite means that there is statistical evidence of outperformance.

$$Accept\ Hypothesis = \frac{\alpha_{StockPickers} - \alpha_{ClosetIndexers}}{\sqrt{\frac{s_1^2}{n} + \frac{s_2^2}{n}}} \leq \text{Z-score}$$

$$Reject\ Hypothesis = \frac{\alpha_{StockPickers} - \alpha_{ClosetIndexers}}{\sqrt{\frac{s_1^2}{n} + \frac{s_2^2}{n}}} > \text{Z-score}$$

Thus accepted H_0 hypothesis means that there is no difference in abnormal net returns between Stock Pickers and Closet Indexers, while a rejected hypothesis means that Stock Pickers outperform Closet Indexers in the sample.

TABLE 22 –TESTING HYPOTHESES FOR LARGER MARKETS

Large Market High Asset Correlation						Large Market Low Correlation	
Stock Pickers						**Stock Pickers**	
EUROPE			**GLOBAL**			**GLOBAL**	
AlphaSP	-0.0004		AlphaSP	-0.0002		AlphaSP	-0.0003
Volatility	0.007		Volatility	0.011		Volatility	0.006
Observations	148		Observations	148		Observations	148
Closet Indexers						**Closet Indexers**	
EUROPE			**GLOBAL**			**GLOBAL**	
AlphaCI	-0.002		AlphaCI	-0.001		AlphaCI	-0.002
Volatility	0.004		Volatility	0.01		Volatility	0.004
Observations	148		Observations	148		Observations	146
H0	2.414316		H0	0.654673		H0	3.366721
Accept?	**No**		**Accept?**	**Yes**		**Accept?**	**No**

Source: Own Contribution [Numbers are from Appendix C.2 and C.3]

In the one-sided hypothesis test where the t-stat for alpha needs to be higher than 1.645 to reject the H_0 hypothesis two out of three tests on the large markets show that retail investors can get significant higher net returns by picking Stock Pickers rather than Closet Indexers.

TABLE 23 – TESTING HYPOTHESES FOR SMALLER MARKETS

Small Market High Correlation

Stock Pickers			
EUROPE		**GLOBAL**	
AlphaSP	-0.0002	AlphaSP	-0.003
Volatility	0.014	Volatility	0.028
Observations	148	Observations	142
Closet Indexers			
EUROPE		**GLOBAL**	
AlphaCI	0.0002	AlphaCI	0.0002
Volatility	0.008	Volatility	0.019
Observations	148	Observations	138
H0	-0.30179	H0	-1.1218
Accept?	**Yes**	**Accept?**	**Yes**

Small Market Low Correlation

Stock Pickers			
EUROPE		**GLOBAL**	
AlphaSP	-0.001	AlphaSP	0.002
Volatility	0.012	Volatility	0.015
Observations	126	Observations	148
Closet Indexers			
EUROPE		**GLOBAL**	
AlphaCI	-0.0004	AlphaCI	0.001
Volatility	0.005	Volatility	0.008
Observations	148	Observations	148
H0	-0.52387	H0	0.715619
Accept?	**Yes**	**Accept?**	**Yes**

Source: Own Contribution [Numbers are from tables in Appendix C.4 and C.5]

None of the H_0 tests are rejected and thus we cannot say that Stock Pickers outperform Closet Indexers in the smaller markets.

7.5 CONCLUSION

The statistical models of various types of active management on the different markets varied a lot. In the larger markets the net abnormal returns from the management types were more polarized, while in smaller markets all the management types delivered very similar abnormal returns.

On both Large Markets with High Correlation and with Low Correlation Global Concentrated funds was the only management type able to exploit statistical significant value with their investment strategy. In both markets they delivered positive abnormal gross returns.

On the Small Markets with High Correlation, only funds categorized with low AS, Factor Bettors were able to deliver significant abnormal gross return. In the Small Global Markets with Low Correlation Stock Pickers and Concentrated managements from the higher AS category were able to outperform, while Closet Indexers from the lower AS category delivered significant alpha.

The barrier for outperforming increases rapidly after adjusted for fees, only four funds deliver abnormal returns that were significantly different than their benchmark after adjusted for risk. All the management types with significant abnormal returns were operating in large markets.

Closet Indexers in Large European Markets with High Correlation significantly underperformed the market after the net abnormal returns were cleaned for systematic risk factors. On the other hand, concentrated funds in Large Global Markets with Low Correlation were able to outperform the market after. On the same market both Closet Indexers and Factor Bettors very significantly underperformed the market.

As a supplement to statistical evaluations on management types against the market, two management types were tested against each other. All the market types were tested with a H_0 that Stock Pickers performed worse or equally to Closet Indexers. On the Larger markets 2 out of 3 hypotheses were rejected, which means that a retail investor could increase his wealth by selecting stock pickers instead of Closet Indexers in these markets. On the Small markets none of the hypothesis were rejected and 3 out of 4 tests gave a negative t-statistics which means that an investor on these markets would get a statistical, insignificant higher return by choosing Closet Indexers instead of Stock Pickers.

8. PERFORMANCE PERSISTENCE

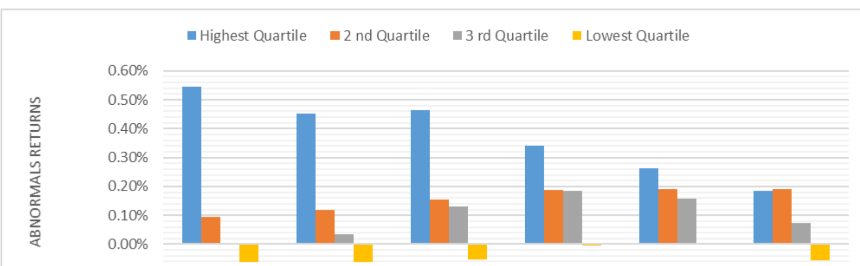
This section gives retail investor information on what his expectation to future returns should be when investing in a mutual fund based on the funds yearly average AS.

In this section the performance persistence of AS is evaluated. The methodology is inspired from Morningstar's article on AS from 2016. Funds are first sorted into quartiles based on their AS in year t and thereafter the quartiles are performance evaluated based on average abnormal returns in the following five-year period. The abnormal return in this analysis is the funds return deducted with the return of its benchmark. For ensuring a realistic setup to when the investor possesses portfolio information which is necessary to calculate AS, the performance evaluation is lagged with two quarters. The performance evaluation is on a rolling basis from 2005 to 2015. The decomposition of funds into large and small markets based on constituents of their benchmark is still current. Consequently, two separate performance evaluations are done – one for funds operating in small markets, and one for funds operating in large markets.

8.1 PERFORMANCE PERSISTENCE ON LARGE MARKETS

All funds that are benchmarked to an index with more than 79 constituents[27] are analyzed for performance persistence in this section.

FIGURE 14 – PERFORMANCE EVALUATION OF AS QUARTILES ON A ROLLING FIVE-YEAR PERIOD



	2005-2010	2006-2011	2007-2012	2008-2013	2009-2014	2010-2015
Highest Quartile	0.54%	0.45%	0.46%	0.34%	0.26%	0.18%
2 nd Quartile	0.09%	0.12%	0.16%	0.19%	0.19%	0.19%
3 rd Quartile	0.00%	0.04%	0.13%	0.18%	0.16%	0.07%
Lowest Quartile	-0.06%	-0.06%	-0.05%	-0.01%	0.00%	-0.06%

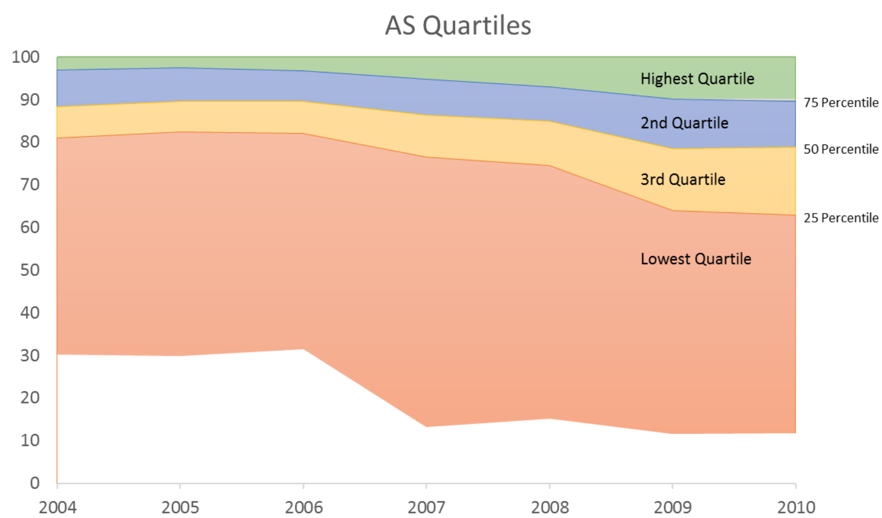
Source: Own Contribution

Funds from the highest AS quartile have outperformed all the other AS quartiles in net abnormal returns in five out of six five-year periods. Conversely, funds from the lowest AS quartile underperform the other AS quartiles in abnormal net return in all the performance periods. However, the difference between the

27 Median of the data sample

highest and lowest AS quartile has decreased over the evaluated period, which implies that the outperformance of high AS could be time dependent.

Figure 15 - AS Level for the quartiles



Source: Own Contribution

Over the evaluated period AS quartiles has decreased in the data. In this data funds with higher level of AS are better represented. Between 75 and 50 percentiles the difference is only of 10 percentages, while the difference between the 25 and 0 percentile is on 51 percentages. The data has a concentration of funds with a high AS. Many active managers are trying to exploit value by taking positions in other systematic risk factors than their benchmark portfolio. Consequently, two performance evaluations are made with the same methodology as interpreted above, but the abnormal returns are cleaned for style biases with a regression on five systematic risk factors of the Fama French model.

Table 24 – Performance evaluation of AS quartiles on Large markets with Fama French five- factors

	Performance Evaluation of Active mutual funds from 2005-2010							
AS Quartiles 2004	**Alpha**	**Market**	**Small**	**Value**	**Robust**	**Conservative**	**# Funds**	**Avg AS**
ASQ1 High	0.0050**	0.046	-0.088	0.140	-0.063	-0.012	50	94.03
ASQ2	0.0010	0.022	0.031	-0.144	-0.180	0.103	49	90.70
ASQ3	0.0010	0.001	-0.003	-0.119	-0.175	0.050	49	83.06
ASQ4 Low	-0.0003	-0.006	-0.043	-0.019	-0.098	-0.033	50	67.20
	Performance Evaluation of Active mutual funds from 2010-2015							
AS Quartiles 2009	**Alpha**	**Market**	**Small**	**Value**	**Robust**	**Conservative**	**# Funds**	**Avg AS**
ASQ1 High	0.0020	-0.009	-0.109	-0.024	-0.038	-0.059	138	93.87
ASQ2	0.0020**	0.012	-0.023	0.065	0.060	-0.042	137	83.94
ASQ3	0.0003	0.021	-0.011	0.047	0.062	0.017	137	71.85
ASQ4 Low	-0.0010**	0.020	-0.014	0.033	0.038	0.046	138	46.25

Note: **p <0.05

Source: Own contribution [From Appendix C, *Table (16.1,16.2)]*

In the first performance evaluation, AS shows evidence of persistent outperformance after taking account for the systematic risk factors on a 95 percent confidence interval. However, on a performance evaluation with the same methodology 5 years after the first, the evidence is not as strong. In this evaluation of the performance the 2nd quartile of AS is the strongest performer and delivers significant risk adjusted abnormal returns in the 95-confidence interval. In this evaluation Closet Indexers are delivering significant negative abnormal returns.

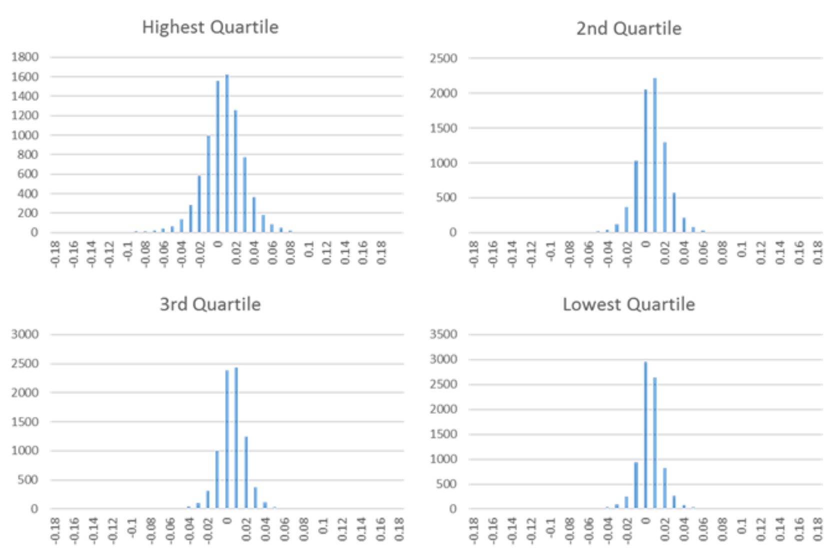
The exposure to the five risk factors of the highest AS quartile is very different in the first performance evaluation. Exposure in Market and HML is positive, while SMB, RMW, CMA all are negative. A positive exposure to SMB indicates that funds from the highest quartile have made concentrated bets in small stocks and have a high SML beta.

In the second performance evaluation, all the systematic risk factors are negative. It is very noticeable that a crisis has been from 2007-2009 and maybe some funds have changed their investment strategy after the reflection of the financial crisis. Lowered their market risk, and increased exposure to large, growth, weak and aggressive stocks that lower the systematic risk of the portfolio.

Distribution of Abnormal Returns

In 2016 Morningstar wrote an article, where they warned investors about using AS as investment tool. In their report they write that dispersion is positive correlated with AS. Consequently a short subsection on the abnormal return distribution of each AS quartile from 2009 will be presented.

FIGURE 16 - DISTRIBUTION OF ABNORMAL RETURNS ON LARGE MARKETS

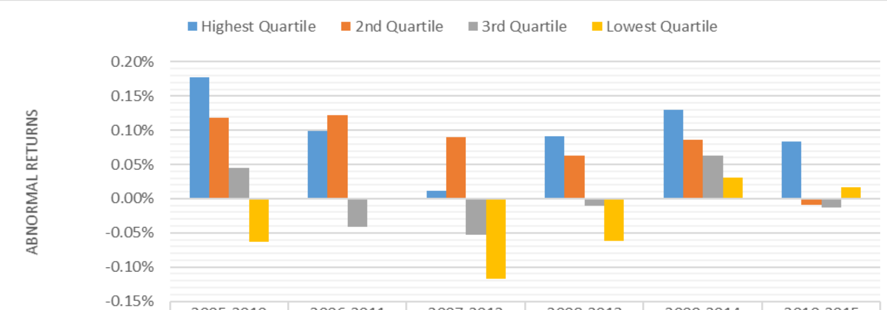


The dispersions of returns are widening with the level of AS, the highest quartile has a much wider distribution than the funds from the lowest quartile of abnormal returns. A wider distribution of abnormal returns means that the volatility is higher for funds in the highest quartile. In the performance evaluation, it was stated that the higher quartiles of AS deliver higher positive abnormal returns, but in the figure it is shown that with these abnormal returns comes also a higher dispersion of the returns.

8.2 PERFORMANCE PERSISTENCE ON SMALL MARKETS

All the funds with a benchmark in the lower percentile of the benchmarks are analyzed in this section with the same approach as used earlier.

FIGURE 17– PERFORMANCE EVALUATION OF AS QUARTILES ON A ROLLING FIVE-YEAR PERIOD

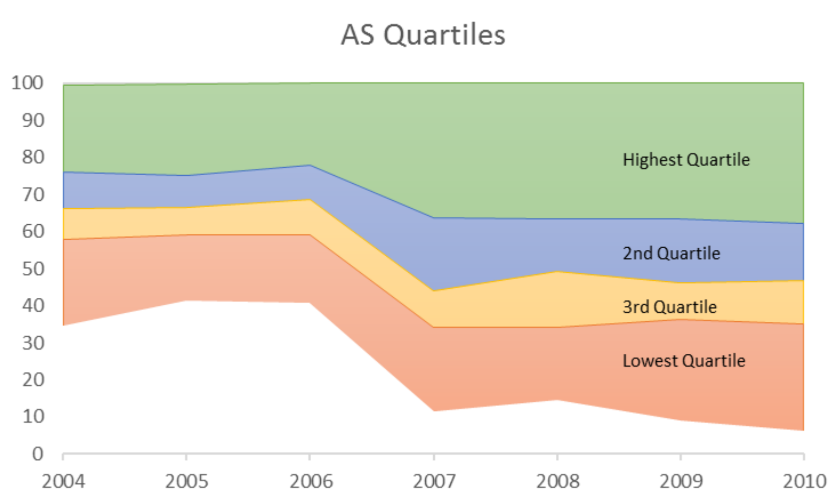


	2005-2010	2006-2011	2007-2012	2008-2013	2009-2014	2010-2015
Highest Quartile	0.18%	0.10%	0.01%	0.09%	0.13%	0.08%
2nd Quartile	0.12%	0.12%	0.09%	0.06%	0.09%	-0.01%
3rd Quartile	0.04%	-0.04%	-0.05%	-0.01%	0.06%	-0.01%
Lowest Quartile	-0.06%	0.00%	-0.12%	-0.06%	0.03%	0.02%

Source: Own contribution

The average abnormal monthly returns for funds on smaller markets are very different from larger markets. Compared to figure 14 of funds operating in large markets, funds in the highest quartile of smaller markets are not as strong performers. The highest AS quartile has been the best performer in 4 out of 6 periods, while the lowest quartile has been the worst performer in 3 out of 6 periods.

FIGURE 18 – AS LEVEL FOR THE QUARTILES



Source: Own Contribution

All the AS quartiles have decreased over the period. The AS level of funds in the 2nd and 3rd quartile lies in a small range, while AS of funds in the highest and lowest quartile are more spread out. All the quartile limits of AS decreased in 2007, which is the year where the financial crisis started. Funds are in a higher degree hugging the benchmark in a crisis than otherwise.

As in the subsection earlier the average abnormal returns are also adjusted for systematic risk factors with the Fama French five-factor model. In this setting Fama French systematic risk factors for European countries are used. The cause is that the coverage ratio of countries used to compute the factors are better represented by European than Global Ex US. Furthermore, the explaining power was higher for the statistical model with European risk factors and this is the basis for the choice. The two performance evaluations are done on AS quartiles from 2004 and 2009.

TABLE 25 - PERFORMANCE EVALUATION OF AS QUARTILES ON SMALL MARKETS WITH FAMA FRENCH FIVE-FACTORS

	Performance Evaluation of Active mutual funds from 2005-2010							
AS Quartiles 2004	**Alpha**	**Market**	**Small**	**Value**	**Robust**	**Conservative**	**# Funds**	**Avg AS**
ASQ1 High	0.0003	0.014	-0.005	0.145	0.305	0.024	28	86.92
ASQ2	0.001	-0.025	-0.041	0.184	0.038	-0.041	27	69.99
ASQ3	-0.0002	0.024	-0.022	0.104	0.126	0.044	28	62.22
ASQ4 Low	-0.001	0.005	-0.027	0.043	0.042	-0.018	27	50.45
	Performance Evaluation of Active mutual funds from 2010-2015							
AS Quartiles 2009	**Alpha**	**Market**	**Small**	**Value**	**Robust**	**Conservative**	**# Funds**	**Avg AS**
ASQ1 High	0.0002	-0.001	-0.031	0.123	0.235	0.107	62	75.99
ASQ2	-0.0005	0.008	0.006	0.069	0.092	0.104	62	54.38
ASQ3	-0.0010	0.011	0.060	0.089	0.139	0.072	62	41.74
ASQ4 Low	-0.0001	0.001	0.036	0.070	0.115	-0.010	62	25.74

Note: **p <0.05

Source: Own contribution [From Appendix C, (17.1,17.2)]

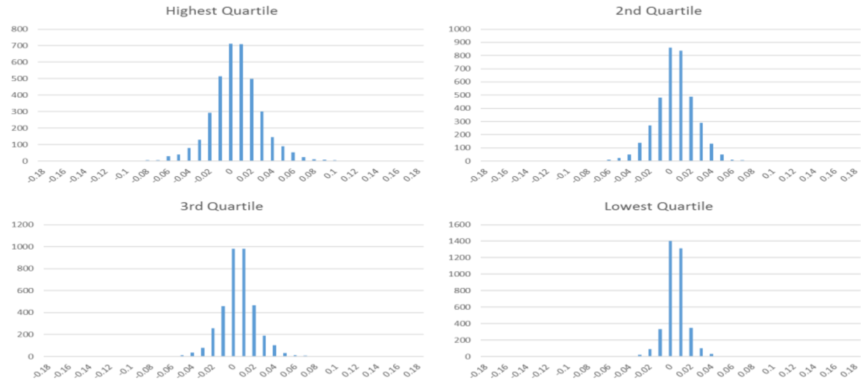
None of the AS quartiles deliver significant net abnormal returns after adjusted for systematic European risk factors in the two performance evaluations. However, the highest AS quartile funds are delivering insignificant positive abnormal net returns in both tests.

In the first evaluation period the highest AS Quartile abnormal net returns is explained as positive by Market excess return, Value, Robust and Conservative factors, while negative by Small factors. In the second evaluation period the highest AS quartiles abnormal return is affected positive by Value, Robust and Conservative factors, while Market excess return and Small factors has a negative effect on abnormal returns in the period.

The drop in the average AS level in the highest quartile between the first and second evaluation is 10.93 percent and the other quartiles has a similar pattern.

Distribution of abnormal returns

FIGURE 19 - DISTRIBUTION OF ABNORMAL RETURNS ON SMALL MARKETS



Since the drop is as large in AS, distribution of abnormal net returns from both evaluation periods are computed. Abnormal returns from AS quartiles in 2009 will be presented here, while from 2004 are shown in appendix.

The tails of the distribution for the highest AS quartile are wider than for all the other quartiles. In the lowest AS quartile the abnormal returns are very concentrated around 0.

8.3 CONCLUSION

The highest AS quartile showed evidence of persistent outperformance in 5-year average abnormal returns both for funds operating in large markets and in small markets. The evidence was stronger on the large market with 5 out of 6 times being the quartile with highest abnormal return. In the lowest quartile of AS, were similar, only opposite patterns observed. Again, the evidence was stronger on the large market where the lowest quartile in 4 out of 6 times was the worst performer.

After performing two separate risk adjusted analyses on the monthly abnormal net returns on two different 5-year periods with the newest Fama French five-factors on both large and small markets, the highest AS quartile from 2004 in large markets, is able to deliver significant alpha in the next 5 subsequent years. The lowest AS quartile, deliver the investor an insignificant negative alpha in the same period. In the second performance evaluation, AS quartiles from 2009, are the 2nd AS quartile on the large market able to generate risk adjusted net abnormal, while the lowest AS quartile delivered significant negative alpha to the shareholders. On the small market the highest quartile of yearly AS from 2004 is delivering an insignificant abnormal net return in the following 5 years after adjusted for risk, while the lowest quartile has an insignificant negative alpha. In the latter performance evaluation, based on AS quartiles from 2009, the same pattern was in the alpha. The highest AS quartile gave a positive insignificant alpha, while the lowest AS delivered an insignificant negative alpha.

In all the analyses there was a tendency that the dispersion of the abnormal returns in the following five years was higher for funds in the highest AS quartiles. Consequently, there is evidence that funds in the higher AS quartiles delivers higher returns, but if the retail investor is risk averse a fund from one of the lower quartiles could be more optimal for him.

9. MODEL DIAGNOSTICS FOR SIGNIFICANT FINDINGS

In this section the models with significant abnormal net returns in the regression model are tested for violations of its assumptions.

Throughout the master thesis many regression models on empirical data are performed. Many of these models had insignificant alpha and they are not test for violations of assumptions. However, there were a handful of models that could not explain positive abnormal returns with systematic risk factors from asset pricing models.

The assumptions for the following models were:

1. **Linearity and additivity**
2. **Statistical independence**
3. **Homoscedasticity**
4. **Normality**

For validating these findings model diagnostics are made for all the assumptions on the linear regression setting. When recommending anything based on a statistical model, it is vital that the assumptions made in the model holds. For example, a risk management department assuming their company's exposure (VAR) to be normally distributed, when their down-side exposure has a long tail, could potentially lead to a default.

First assumption is tested with eyeballing the predicted values of the model against the independent variables, and furthermore a Variance Inflation Factor (VIF) test is used to strengthen the findings. Second assumption is tested with a Durbin Watson test on the data, which is used to test for autocorrelation in the model. Third assumption is tested by analyzing the plots of the predicted values versus the residuals of the models. Fourth assumption is tested by eyeballing a Normal Q-Q plot, but furthermore a Jarque-Bera and a Shapiro test is used for concluding if the normality holds.

TABLE 26 – MODEL DIAGNOSTICS OF SIGNIFICANT ALPHA MODELS

Model				Assumption			
Market	**Characteristics**	**Group**	**Alpha**	**Linearity (1)**	**Statistical independence (2)**	**Homoscedasticity (3)**	**Normality (4)**
Full Sample	None	Concentrated	Positive**	Holds	Holds	Holds	Holds
Large	High Correlation	EU Closet Indexers	Negative***	Holds	Holds	Holds	Violated
Large	Low Correlation	Global Concentrated	Positive**	Holds	Holds	Holds	Holds
Large	Low Correlation	Global Closet Indexers	Negative***	Holds	Holds	Holds	Violated
Large	Low Correlation	Global Factor Bettors	Negative**	Holds	Violated	Holds	Violated

Note: ** p-value < 0.05, *** p-value < 0.01

Source: Own Contribution [From Appendix D.1]

Some of the assumptions made on the statistical model were violated when testing the empirical data. Global Factor Bettors in Large Markets with Low Correlation had an error term that was statistical negative autocorrelated with the lagged residual. Furthermore, the group violated the normality assumption by rejecting both the Jarque-Bera and Shapiro H_0 hypothesis on normality.

The normality test was also violated by two others models, European Closet Indexers on Large Markets with High Correlation and Global Closet Indexers on Large Markets with Low Correlation.

Violation of normality assumption means that the distribution has a larger tail than the normal distribution assumes. The consequence of this can be that a few residuals have a large impact on the parameters in the model that could lead to biases in the model. A violation of the normal distribution can be fixed by Box-Cox transforming the dependent variable or transforming the independent variables with log or square root.

Concentrated funds from the Full Sample and on the Large Market with Low Correlation are able to pass all the violation tests made on the data.

TABLE 27 – MODEL DIAGNOSTICS OF SIGNIFICANT MODELS ON AS QUARTILES

Model				Assumption			
Market	**AS Quartile**	**Year**	**Alpha**	**Linearity (1)**	**Statistical independence (2)**	**Homoscedasticity (3)**	**Normality (4)**
Large	Highest	2004	Positive**	Holds	Holds	Holds	Holds
Large	2nd	2009	Positive**	Holds	Holds	Holds	Holds
Large	Lowest	2009	Negative**	Holds	Holds	Holds	Holds

Note: ** p-value < 0.05

Source: Own Contribution [From Appendix D.2]

For the statistical models in the persistence section of AS, all the assumptions made on the models pass in model diagnostics. However, it is hard for a retail investor to take advantage of the information on statistical information in the table, since the statistical significant positive abnormal returns comes from two different quartiles of AS. However, there seems to be a pattern that significant outperformance is more frequently occurring in the higher AS Quartiles.

10. CONCLUSION

This section summarizes all the most vital results of this empirical study. By connecting all the conclusions of the sub-questions, a conclusion to the main problem statement is presented.

The section is structured to systematically answer all the sub-questions and secondly, and vitally, the overall problem statement. In terms of the sub-question 1) *"Are there specific fund managers in the sample, which significantly outperforms in all markets?"* It was found that all the management types, except Factor Bettors, could beat the market in average when using gross returns. Factor Bettors had insignificant t-statistics on gross returns when adjusting for the Five factor model, but with the other two performance models their returns were significant. After adjusted for fees, all abnormal returns from the different management types, except the group of Concentrated funds, became insignificant. However, after analyzing the benchmarks ratio in each group, concern was raised that a funds AS level was affected by the structure of its benchmark; funds with high AS had many constituents in their benchmark, while funds with low level of AS had few constituents.

Sub-question 2) *"What are the implications by using AS and TE on different investment markets?"* A Monte Carlo simulation model was developed to break down the causality between a fund's portfolio, its benchmark and its AS level. The model assessed a positive correlation between the size of the benchmark in terms of constituents and AS. Furthermore, a negative relationship was stated between the size of the fund's portfolio and AS. Through the lenses of my Monte Carlo simulation the definition of Cremers & Petajisto (2009) of a 60 percent AS limit to differentiate between Stock Pickers and Closet Indexers is not reliable on all market types. When assessing a universal definition of a concept to screen funds that outperform, it is vital that funds worldwide compete on the same playing field. Funds operating on smaller markets are affected by using an absolute AS level to distinguish between the management types, since they will have a higher tendency to be characterized as Closet Indexers than funds operating on larger markets. Moreover, an analytical approach was made to derivate the mathematical equation of TE to declare a relationship between average cross correlation in the benchmark and TE. The derivation was ambiguous and could not clarify a relationship between TE and average asset correlation on the market.

The heterogeneous playing fields of the funds lead to sub-question 3) *"Are AS and TE as investment tool for screening funds that outperform the market better to use on some markets than others?"* The benchmark of the funds represented the market they are domiciled in. Thus, all the benchmarks were sorted into 4 equally weighted portfolios; first after size in terms of constituents and then after average cross correlation between the assets in the benchmark index.

Especially the size of the funds benchmark had vital influence on the findings. On larger markets Cremers & Petajisto (2009) finding high AS funds outperforming low AS funds in risk adjusted abnormal net return was reflected. Closet Indexers underperformed the benchmark with a significant t-statistic, while Concentrated funds significantly outperformed the benchmark. On smaller markets, none of the management types had risks adjusted net abnormal returns. In risk adjusted gross abnormal returns, the findings on smaller markets were contrary to Cremers & Petajisto (2009), here the best performers were management types with low AS.

The retail investors' use of especially AS as Investment tool should solely be used on larger markets, where funds with low AS in a higher degree reflect an active management strategy on stock selection against the benchmark. A fund manager that uses a benchmark index that has many different stocks to select from can take many active bets against it and still hold a well- diversified portfolio of stocks. Thus a low AS on these markets is a strategic choice made by the management to be a Closet Indexer. On the smaller markets, take for example a fund benchmarked to MSCI Denmark, the index consists of only 16 stocks and thus the management needs to take positions in almost all the stocks to get a well-diversified portfolio. The objective of retail investors when they use mutual funds is to get a well-diversified portfolio, thus a low AS on the small markets is not necessarily a Closet Indexer, but more a management going for diversification in the index. In the performance evaluation of the market types there also seems to be evidence of this, since Cremers & Petajisto (2009) findings are better reflected on larger markets, while on smaller markets AS seems to have no predictive power of the performance of the funds.

A deeper view into performance of Stock Pickers and Closet Indexers lead to sub-question 4) *"Have Stock Pickers outperformed Closet Indexers in risk adjusted abnormal net returns on the different markets?"* A statistical hypothesis test was established with the H_0 hypothesis that Closet Indexers were performing equally abnormal net returns to Stock Pickers on the four different market types. On the larger markets, two out of three groups of Stock Pickers rejected the H_0 hypothesis and thus outperformed Closet Indexers. On the smaller markets, none of the four groups of Stock Pickers could reject the H_0 hypothesis and thus were no evidence that Stocks Pickers outperformed Closet Indexers on smaller markets. The evidence is the same as for sub-question 3), on larger markets high AS funds outperform low AS funds, while there is no evidence of outperformance on smaller markets. Cremers & Petajisto (2009) AS limit to distinguish between Stock Pickers and Closet Indexers seems to be biased on smaller markets, since funds characterized as Closet Indexers perform equally well as Stock Pickers on smaller markets.

Sub-question 5) *"Can a retail investor, who uses yearly AS as investment tool, increase his expected return for the following 5 years?"* In this section funds in the highest AS quartile showed evidence of outperformance from 2005 to 2010 based on the subsequent 5-year average net abnormal returns in both large and small markets. The evidence was clearer on the large markets where the highest AS quartile outperformed all the other AS quartiles in 5 out of 6 times. Two of the 5-year abnormal return periods from the AS quartiles were risk adjusted with the Fama French five-factor model. In the first performance evaluation, the highest AS quartile from 2004 showed significant positive risk adjusted net abnormal returns in the following 5-year period. In the second evaluation, the 2nd highest AS quartile from 2009 showed significant positive risk adjusted net abnormal returns, while the lowest AS in 2009 had significant negative risk adjusted abnormal returns in the 2010-2015 period. However, analysis of the abnormal returns of the AS quartiles showed that dispersion was much higher for the higher AS quartiles than for the lower AS quartile, so there is a higher volatility for investors choosing high AS funds on larger markets. On the small markets, the highest AS quartile was the best performer in 4 out of 6 performance evaluation periods based on average from the following 5 years of abnormal net returns. The procedure thereafter was the same as for the large markets, and all the 60 monthly observations of abnormal net returns in each AS quartile from 2004 and 2009 were risk adjusted with the Fama French five-factors. In the risk adjusted regressions none of the models gave significant risk adjusted abnormal net returns.

An analysis of the abnormal net returns distribution of the different AS quartiles, as performed on the large markets, showed that higher AS quartiles had more dispersion in their abnormal net returns than lower AS quartiles. Subsequently, retail investors should be aware that dispersions in returns increase when investing into high AS funds. Additional information on AS is that from 2006 to 2007 there was a large decrease in the limits of AS in each AS quartile on the small market sample; the financial crisis started in 2007 and this indicates that AS is time dependent and in crisis funds are not taking as many active bets against the benchmark as usual. For answering sub-question 5) there seems to be some persistent performance in AS, which the retail investor can use to increase his expected returns in the following years. The evidence of outperformance was clearer on the large markets by the highest AS quartile than on the small markets. However, in both markets an increase in AS lead to a higher dispersion in the abnormal returns, which leads to a higher volatility for the returns of the retail investor when using AS as investment tool.

The sub-questions all lead to the main problem statement.

Through the lenses of AS and TE the only type of management that delivered significant risk adjusted abnormal net returns was Concentrated funds, the other management types were insignificant. However, when analyzing the methodology behind AS with a numerical model a relationship was stated between the structure of the benchmark and the funds AS level. My data sample consisted of 29 different benchmark structures, which raised a concern of the universal 60 percent limit of AS to distinguish between high AS and low AS funds. Thus, the funds were decomposed into 4 different market types based on size and average cross correlation of their benchmark, where the same performance methodology was used on all the markets. Investing through the lenses of AS and TE generated very different results depending on what market it was. Especially on the smaller markets there were no evidence that a retail investor could get higher expected abnormal net returns by investing in high AS funds. On the larger markets a retail investor could get higher expected abnormal net returns by investing into a high AS Concentrated fund in the Large Market with Low Correlation. Moreover, low AS funds performed significant negative risk adjusted abnormal returns in three out of six groups on the larger markets. An H_0 hypothesis test was also established to find if high AS funds outperformed low AS funds on the different markets. In the larger markets, Stock Pickers outperformed Closet Indexers in 2 out of 3 cases. In the smaller markets, Stock Pickers outperformed Closet Indexers in none of the cases. There seems to be a tendency that high AS outperform low AS funds only is consistent with Cremers & Petajisto (2009) definition of high and low AS by the 60 percent limit to distinguish them only is reflected on the larger markets. AS also showed evidence of persistence on larger markets, but funds in the higher AS quartiles had a higher dispersion of abnormal returns. From this sample, it is ambiguous if a retail investor could increase his expected abnormal net returns, but the investors should only use AS in the context of Cremers & Petajisto (2009) on large markets. Furthermore a retail investor, trying to increase his expected abnormal return by using AS and TE, should be aware that it comes with the price of a higher volatility.

10.1 FUTURE RESEARCH

This report raises several potential problem areas for future research on the subject. Additional improvements on the statistical models could be made, so that all the assumptions were fulfilled on parameters of the model. In addition to the unconditional performance models used throughout the report, a conditional performance model would be interesting to use for comparing the findings to each other. In terms of the active management types a more complex sorting methodology in form of Petajisto (2013) or for example using a fixed limit, conditional of the benchmark, to distinguish between high and low AS funds, would be an interesting approach for further study.

11 DISCUSSION

This section establishes a discussion of Active Share and furthermore presents a brief introduction of the newest trend in asset management, subsequently it links Active Share with it.

Discussion of Active Share

In the report an assumption was made that funds only invest in stocks, which is part of their benchmark index. In studies on AS, AS has been computed based on a benchmark index, which best reflect the fund's investment activity in terms of stocks. For example, Cremers & Petajisto (2009) used 19 different benchmark indices and used the index with the lowest AS. This best fit approach used to compute AS shows a tendency that many active mutual funds are in a grey zone and does also invest in stocks outside their benchmark, which biases AS upwards.

The issue with funds investing outside the benchmark is complex and can be perceived as comparing apples with oranges, because while some funds merely invest in stocks that are within their benchmark, other funds only invest in a part of the stocks in their benchmark.

For example, in small investment universes a fund could have a high AS only due to high investment activity that is outside of their benchmark, while another fund with exactly the same investment strategy, which only invest in the benchmark, will be classified as a low AS fund. There are some evidence pointing towards this is the case on smaller markets. The Monte Carlo model [6.2] showed that funds with a portfolio size of 15 that operates on market with 30 stocks should not be able to have an AS higher than 56. Nonetheless there are still some funds that are benchmarked to MSCI Denmark and have an AS over 68 percent [Sparinvest Danske Aktier]. A retail investor should take into consideration if the funds AS comes from positions within the index or outside of the index.

Another parameter that affects AS which is not related to the funds' investment strategy is the cash position, which is part of its holdings only to meet the shareholders demand for redemption (Chernenko & Sunderam, 2016). It is expected that funds hold 5.8 percent of their assets under management in cash (Yan, 2006). In the AS terminology holding a cash position is seen as an active bet against the fund's benchmark, which thereby leads to a higher AS despite the fact that cash only is hold for operational purposes in most cases.

Based on the problems above the formula presented by Cremers & Petajisto (2009) has been criticized for being misleading to the investors, since fund managers also deliberately can manipulate their AS. This has led to a new updated version of the formula by Cremers (2016) that better demonstrates the pitfalls of AS.

$$AS = 100\% - \sum_{i=1}^{N} Min\left(w_{fund,i}, w_{benchmark,i}\right) x\ d[w_{fund,i} > 0] \quad (30)$$

This formula better shows that investments outside the benchmark affects AS upwards, where d$[w_{fund,i} > 0]$ is an indicator variable equal to 1 for all long positions by the fund (not short) and 0 otherwise. The results for the new formula on AS are identical to Cremers & Petajisto's (2009), but in a higher degree emphasizes that AS is only lowered by overlapping positions that are both in the fund's portfolio and in its benchmark.

The use of Active Share

The results in this report pointed out some structural leaks of AS, which makes investment approaches entirely based on AS supported by TE inappropriate for retail investors. Wittman et al. (2013) and Khusainova & Mier (2013) points out that AS is affected by the structure of the benchmark and therefore the investment universe needs to be taken into consideration when interpreting the fund's AS level. Especially on smaller investment markets a high AS can be unreachable by mutual funds unless a compromise is made with the objective of holding a well-diversified portfolio. Despite this, in Nordic countries, which are composed of smaller investment markets, regulators have shown a great interest in AS. In 2013 the Danish FSA (2013) performed a study on active funds with Cremers & Petajisto's (2009) 60 percent AS limit combined with a 4 percent TE limit in order to distinguish between real active funds and "Closet Indexers". The report concluded that 56 out of 188 funds not delivered the activity level expected from active funds. This led to the Danish Investment Fund Association (IFB) to question how the danish FSA can draw realistic conclusions, when they are only looking at two key indicators and without speaking directly to the funds. After at dialogue between IFB and the danish FSA the limit of AS was redefined and lowered to 50 percent for a Closet Indexer on the danish market (FSA, 2016) [7]. In Norway, the Financial Supervisory Authority in 2015 published that DNB had failed to prove sufficiently active management, even though it had been marketed as such. Norway's FSA demanded DNB to cut the fees or to ensure proper active management. DNB respond by rearranging their portfolio holdings to ensure that the fund could be classified as active and by reducing their fee, which was said to be a consequence of higher competition [8]. Nevertheless this was not enough satisfactory for Norway's Consumer Council, which in addition demanded a repayment of about $80 million dollars on behalf of 180.000 investors. A similar case has been witnessed in Sweden when a class-action lawsuit was filed based on a low AS level, when two active funds of Swedbank Roburs (one of largest funds houses in Sweden) were sued. The Investors were unsatisfied with the underperformance by the two funds combined with low AS levels, which placed the two funds as Closet Indexers [6]. Aktiespararna (the group of retail investors that sued Swedbank) argued that Swedbank had sold them an index fund in reality, but an active fund in terms of fees. Consequently, the investors had paid 7 billion SEK to much in fees over the 10-year period [6].

Regarding active management on smaller markets, one vital question is: *Is Active Share and Tracking Error useless as investments tools in smaller investment universes?*

Even though my master thesis does not provide any evidence of that AS & TE levels are able to identify any specific management type that outperform on the smaller markets, there still could be evidence of this with the application of another methodology on the data. For instance, Petajisto (2013) polarizes specific management types and uses a moderately active management category to explain all the funds placed in the middle with a two-dimensional sorting of AS and TE with five relative quantiles. In the Cremers & Petajisto (2009) methodology all these moderately active funds are either categorized as Stock Picker, Concentrated, Closet Indexer or Factor Bettor. Thus some moderately active funds have been categorized as Closet Indexers and can have affected the performance evaluation of Cremers & Petajisto (2009) definition of Closet Indexers upwards. Also some moderately active funds have been categorized as Stock Pickers and these funds might have affected the category downwards. In result, retail investors should not trust these findings blindly, since specific management types on smaller investment markets perhaps with another research design can outperform.

The future of Asset Management

Lastly I want to discuss the newest trend in asset management, which is a hybrid between passive and active management. The strategy uses the transparency known from passive management and the factor exposure of active management to enhance risk-adjusted returns Ang (2015). Smart Beta strategies are making it easier to bet on risk premiums in an understandable manner for retail investors. The new method of indexing also makes it easier to evaluate active managers', especially factor bettors and Concentrated funds, which are management types that are difficult to evaluate with a market cap index, since they are exposed to segments of the index. For example, they could be exposed to value and size factors within their market cap benchmark. However, with the new smart beta strategies traditional indices are decomposed into factors. For instance, the traditional MSCI World index also comes in the form of MSCI Volatility, Size, Momentum and others. Thus, the financial instruments from smart beta strategies increase the transparency of performance of active managers, because now the managers can be benchmarked to factors. Winther & Steenstrup (2015) use the term smart alpha for active managers that outperform their smart beta benchmarks, and argue that there is still value in active investment strategies. Smart beta strategies are rule based and thus some suboptimal asset allocations are done to represent the factors, thus there are still value in active management within these investment universes (Winther & Steenstrup, 2015).

Active share in a new shape and with another purpose?

To return to the subject, perhaps active share in the future could be decomposed into several entities with smart beta indexes used as benchmarks.

For example: The AS level for an active fund on the MSCI World index

$$AS\ Volatility = \frac{1}{2}\sum_{i=1}^{N} |\omega_{fund,i} - \omega_{MSCIWorldVolatility,i}| \tag{31}$$

$$AS\ Size = \frac{1}{2}\sum_{i=1}^{N} \left|\omega_{fund,i} - \omega_{MSCIWorldSize,i}\right| \tag{32}$$

$$AS\ Momentum = \frac{1}{2}\sum_{i=1}^{N} \left|\omega_{fund,i} - \omega_{MSCIWorldMomentum,i}\right| \tag{33}$$

In this setting a high AS on all factors would most likely represent a Stock Picker or Closet Indexer on the MSCI World market cap index, while a low AS in one or more factors would represent a Factor Bettor or Concentrated fund on the market cap index. The approach does not predict any performance, but gives the investor information about the fund's specific factor bets against the market cap index.

The end

Overall my judgement of Active Share is that this relative new concept, which has made active management more transparent and given retail investors an investment tool to search for indication of outperformance. Asset management is highly complex, therefore a relative simple measure in form of AS does not solely explain the performance puzzle, rather it should more be seen as a criterion that needs to be fulfilled in order to outperform the benchmark; nothing ventured, nothing gained. My final advice to a retail investor, who wants to expand his portfolio with an equity fund based on Cremers & Petajisto's (2009) methodology, is to further investigate the fund's investment universe and its portfolio holding.

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APPENDIX A – AS ON THE FULL SAMPLE

Table A.1: *Example of AS Methodology [Inspiration from Morningstar]*

	Asset Allocation %				
Stock	Fund	Benchmark	Diff[Asset Allocation]	AS	Total AS
Novo Nordisk B	25.00	39.13	-14.13	7.065	34.55
Danske Bank	6.00	8.85	-2.85	1.425	
Vestas Wind Systems	4.00	8.18	-4.18	2.090	
Pandora	3.00	6.21	-3.21	1.605	
Carlsberg B	9.00	4.47	4.53	2.265	
Novozymes B	2.00	4.44	-2.44	1.220	
AP Moller Maersk B	2.00	4.30	-2.30	1.150	
DSV	10.00	4.20	5.80	2.900	
Genmab	20.00	4.01	15.99	7.995	
Coloplast B	3.98	3.98	0.00	0.000	
ISS	0.00	2.98	-2.98	1.490	
Christian Hansen Holding	5.00	2.66	2.34	1.170	
AP Moller Maersk A	0.00	2.46	-2.46	1.230	
TDC	3.00	2.02	0.98	0.490	
William Demant Holding	4.00	1.09	2.91	1.455	
Tryg	3.02	1.02	2.00	1.000	

Table A.2: *Correlation between average AS and constituents on observations from 31/05-2015*

Market	Avg AS	Constituents
ACWI Ex USA	89,14	1859
AC Asia Pac Ex JPN	78,44	943
EM Europe	45,25	836
AC Asia Pacific	77,74	705
AC Asia Ex Japan	78,95	625
Europe Ex UK	74,84	447
Europe	71,25	335
Japan	66,58	318
BRIC	61,98	306
EMU	60,00	241
China	56,16	151
EM	72,81	119
Frontier Markets	68,96	117
Korea	60,67	107
EM Latin America	63,52	83
India	60,67	74
Australia NR	51,89	73
Nordic Countries	63,51	68
Brazil	57,88	60
Hong Kong	79,51	44
Switzerland	36,39	38
Thailand	41,47	34
Indonesia	39,47	31
Sweden	46,34	30
Spain	56,33	25
Italy	45,92	24
Turkey	42,35	24
Russia	43,60	21
Denmark	53,64	16

Correlation	**0,5947**

Figure A.1 – *Distribution of AS & TE for Stock Pickers*

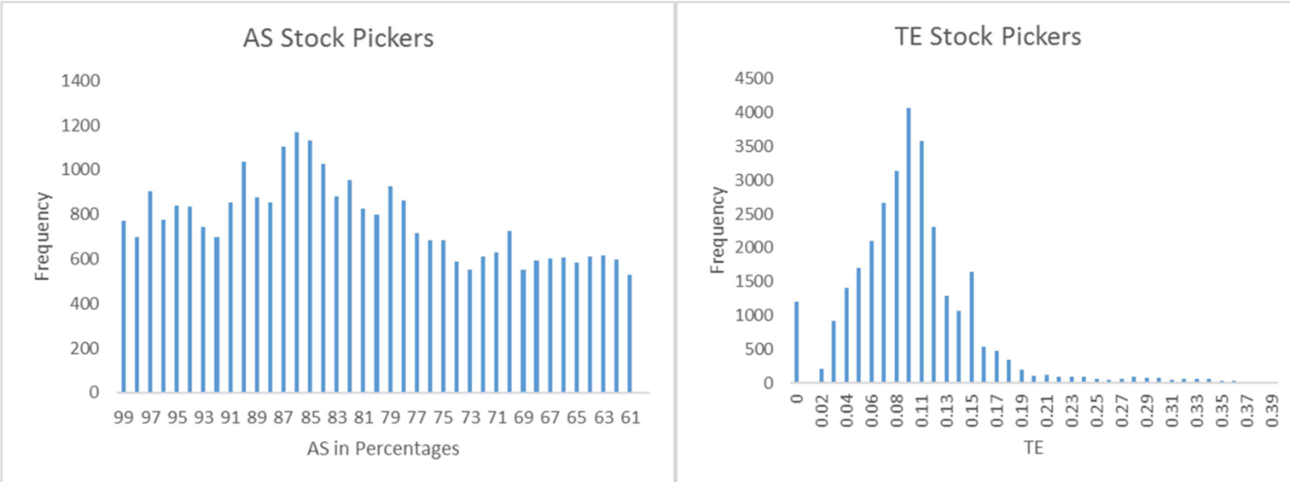


Figure A.2 – *Distribution of AS & TE for Concentrated*

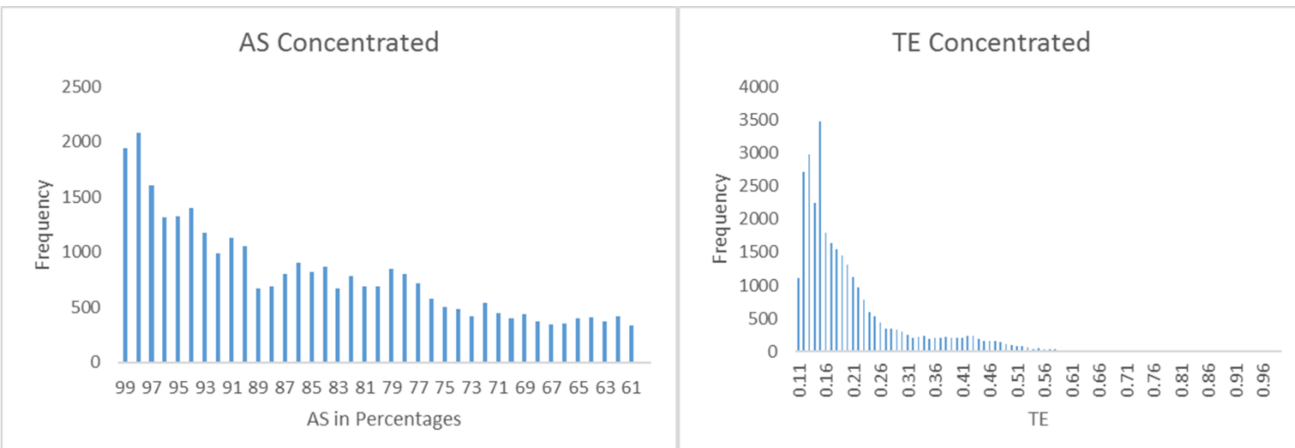


Figure A.3 – *Distribution of AS & TE for Closet Indexers*

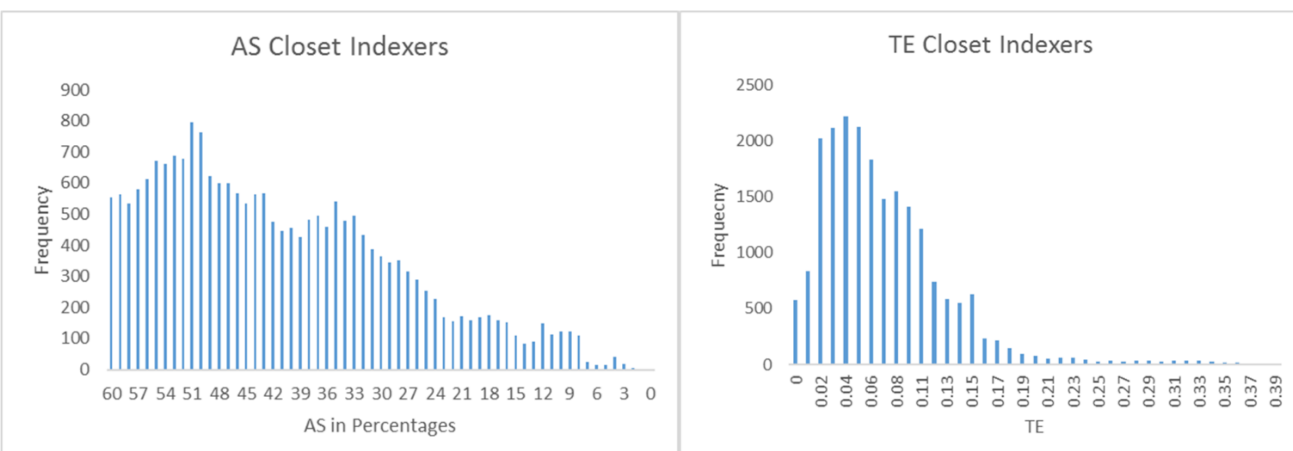
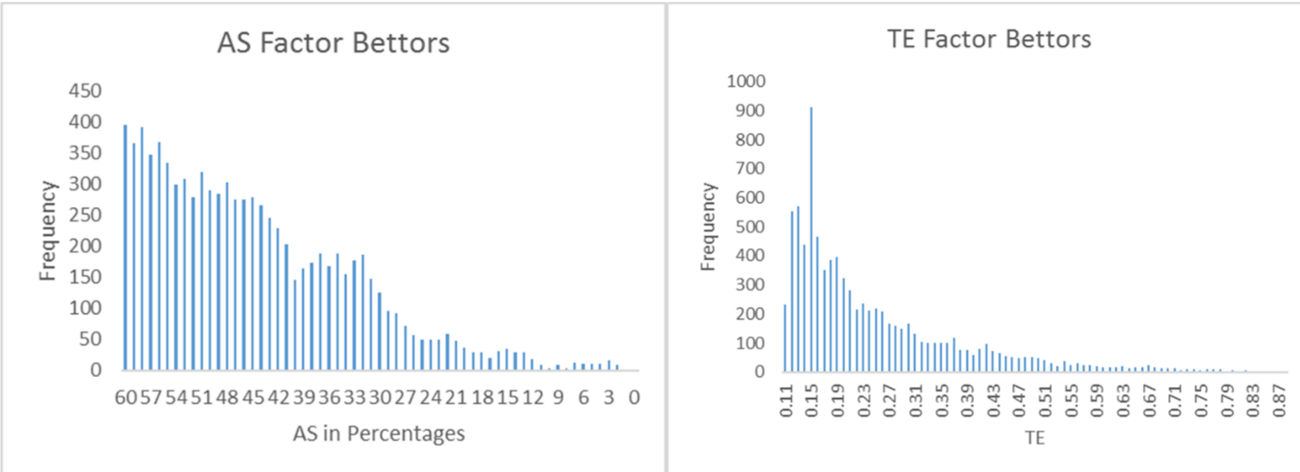


Figure A.4 – *Distribution of AS & TE for Factor Betters*



APPENDIX B – SORTING BENCHMARKS

Table 1.B – *Random Generator for Large Samples*

Equity	Security Name	Closing Weight	n	Random Generator	Random Equity Sample
1	TOTAL	2.88%		N	
2	ANHEUSER-BUSCH INBEV	2.79%		240	
3	SANOFI	2.62%		*Uniform distribution*: $X \sim U[1, 240]$	
4	SIEMENS	2.25%	n	Random Generator	Random Equity Sample
5	SAP	2.17%	1	88	HENKEL STAMM
6	BAYER	2.16%	2	40	VOLKSWAGEN VORZUG
7	ALLIANZ	2.02%	3	165	VOLKSWAGEN STAMM
8	UNILEVER NV (NL) CERT	2.00%	4	216	COVESTRO
9	BASF	1.94%	5	204	TELEFONICA DEUTSCHLAND
10	BANCO SANTANDER	1.83%	6	220	ICADE
11	DAIMLER	1.76%	7	80	KERING
12	BNP PARIBAS	1.57%	8	149	GALP ENERGIA SGPS B
13	DEUTSCHE TELEKOM	1.54%	9	142	ALTICE A
14	AXA	1.32%	10	96	FERROVIAL
15	ING GROEP	1.30%	11	150	GROUPE EUROTUNNEL
16	L'OREAL	1.29%	12	20	DANONE
17	TELEFONICA	1.25%	13	146	TENARIS (IT)
18	LVMH MOET HENNESSY	1.22%	14	232	FRAPORT
19	BBVA	1.15%	15	158	SCOR
20	DANONE	1.12%	16	218	CNP ASSURANCES
21	ENI	1.05%	17	176	REXEL
22	VINCI	1.02%	18	107	AENA
23	AIR LIQUIDE	1.01%	19	132	GAS NATURAL SDG
24	INDITEX	1.00%	20	157	ARKEMA
25	AIRBUS GROUP	1.00%	21	53	HENKEL VORZUG
26	ASML HLDG	0.99%	22	218	FUCHS PETROLUB VORZUG
27	IBERDROLA	0.99%	23	10	BANCO SANTANDER

Table 2.B: *Coverage ratio for calculating average cross correlation for each MSCI index*

Data Coverage for Estimating Average Asset Correlation			
Benchmark	Constituents	Fullfilled Selection Criteria	Coverage of Benchmark
MSCI ACWI Ex USA	1859	38	2%
MSCI AC Asia Pacific	943	48	5%
MSCI EM	836	44	5%
MSCI AC Asia Pacific Ex Japan	705	46	7%
MSCI AC Asia Ex Japan	625	45	7%
MSCI Europe	447	50	11%
MSCI Europe Ex Uk	335	38	11%
MSCI Japan	318	49	15%
MSCI BRIC	306	37	12%
MSCI EMU	241	46	19%
MSCI China	151	44	29%
MSCI EM Latin America	119	47	39%
MSCI Frontier Markets	117	40	34%
MSCI Korea	107	29	27%
MSCI EM Europe	83	46	55%
MSCI India	74	50	68%
MSCI Australia	73	68	93%
MSCI Nordic Countries	68	64	94%
MSCI Brazil	60	49	82%
MSCI Hong Kong	44	36	82%
MSCI Switzerland	38	35	92%
MSCI Poland	38	20	53%
MSCI Thailand	34	29	85%
MSCI Indonesia	31	28	90%
MSCI Sweden	30	28	93%
MSCI Spain	25	24	96%
MSCI Turkey	24	24	100%
MSCI Italy	24	19	79%
MSCI Russia	21	14	67%
MSCI Denmark	16	14	88%

Table 3.B: *Overview of Markets*

#Only MSCI Indexes

Large Markets with High Asset Correlation			
Benchmark	#Funds in Benchmark	#Constituents	Average Correlation
MSCI Europe	101	447	0.3510
MSCI Japan	27	318	0.3370
MSCI EMU	66	241	0.3237
MSCI EM Europe	16	83	0.3065
MSCI Europe Ex UK	15	335	0.2922
MSCI China	10	151	0.2914
MSCI Korea	5	107	0.2736
Total Funds in Sample	240		

Large Markets with Low Asset Correlation			
Benchmark	#Funds in Benchmark	#Constituents	Average Correlation
MSCI EM Latin America	7	119	0.2540
MSCI BRIC	17	306	0.2473
MSCI AC Asia Pacific Ex Jap	16	705	0.2335
MSCI AC Asia Ex Japan	25	625	0.2313
MSCI ACWI World Ex USA	311	1859	0.2304
MSCI EM	55	836	0.2153
MSCI AC Asia Pacific	23	943	0.1925
MSCI Frontier Markets	3	117	0.1117
Total Funds in Sample	457		

Small Markets with High Asset Correlation			
Benchmark	#Funds in Benchmark	#Constituents	Average Correlation
MSCI Russia	28	21	0.6130
MSCI Turkey	3	24	0.5626
MSCI Spain	18	25	0.4878
MSCI Italy	33	24	0.4302
MSCI Poland	4	38	0.4248
MSCI Sweden	39	30	0.4070
MSCI Thailand	3	34	0.4008
Total Funds in Sample	128		

Small Markets with Low Asset Correlation			
Benchmark	#Funds in Benchmark	#Constituents	Average Correlation
MSCI India	43	74	0.3688
MSCI Nordic Countries	10	68	0.3440
MSCI Switzerland	69	38	0.3206
MSCI Brazil	5	60	0.2970
MSCI Indonesia	2	31	0.2949
MSCI Hong Kong	7	44	0.2836
MSCI Australia	3	73	0.2667
MSCI Denmark	28	16	0.2290
Total Funds in Sample	167		

Table 4.B: *Factors used on benchmark*

Large Markets High Correlation

Benchmark	Market Factors
MSCI Europe	Europe
MSCI EMU	Europe
MSCI Europe Ex UK	Europe
MSCI Japan	Global Ex USA
MSCI EM Europe	Global Ex USA
MSCI China	Global Ex USA
MSCI Korea	Global Ex USA

Large Markets Low Correlation

Benchmark	Market Factors
MSCI EM Latin America	Global Ex USA
MSCI BRIC	Global Ex USA
MSCI AC Asia Pacific Ex Japan	Global Ex USA
MSCI AC Asia Ex Japan	Global Ex USA
MSCI ACWI World Ex USA	Global Ex USA
MSCI EM	Global Ex USA
MSCI AC Asia Pacific	Global Ex USA
MSCI Frontier Markets	Global Ex USA

Small Markets High Correlation

Benchmark	Market Factors
MSCI Spain	Europe
MSCI Italy	Europe
MSCI Sweden	Europe
MSCI Russia	Global Ex USA
MSCI Turkey	Global Ex USA
MSCI Poland	Global Ex USA
MSCI Thailand	Global Ex USA

Small Markets Low Correlation

Benchmark	Market Factors
MSCI Nordic Countries	Europe
MSCI Switzerland	Europe
MSCI Denmark	Europe
MSCI India	Global Ex USA
MSCI Brazil	Global Ex USA
MSCI Indonesia	Global Ex USA
MSCI Hong Kong	Global Ex USA
MSCI Australia	Global Ex USA

APPENDIX C – REGRESSION OUTPUTS

//All outputs are made with Hlavac, Marek (2015). stargazer: Well-Formatted Regression and Summary Statistics Tables. R package version 5.2. http://CRAN.R-project.org/package=stargazer.

C.1- Regression Outputs for the Full Sample

Table C.1 – Jensen's alpha for Full Sample

	Abnormal Return	
	Benchmark Adjusted Gross	Benchmark Adjusted Net
Alpha	0.002	0.0001
	t = 4.578***	t = 0.335
Mkt-Rf	0.008	0.008
	t = 1.216	t = 1.206
Observations	148	148
R^2	0.010	0.010
Adjusted R^2	0.003	0.003
Residual Std. Error (df = 146)	0.004	0.004
Note:		*p<0.1; **p<0.05; ***p<0.01

Table C.1.1 – Jensen's alpha for Stock Pickers

	STOCK PICKERS	
	Benchmark Adjusted Gross	Benchmark Adjusted Net
Alpha	0.001	−0.0002
	t = 3.316***	t = −0.568
Mkt-Rf	−0.001	−0.001
	t = −0.199	t = −0.205
Observations	148	148
R^2	0.0003	0.0003
Adjusted R^2	−0.007	−0.007
Residual Std. Error (df = 146)	0.004	0.004
Note:		*p<0.1; **p<0.05; ***p<0.01

Table C.1.2 - Jensen's alpha for Concentrated

	CONCENTRATED	
	Benchmark Adjusted Gross	Benchmark Adjusted Net
Alpha	0.002	0.001
	t = 4.750***	t = 2.112**
Mkt-Rf	0.012	0.012
	t = 1.144	t = 1.124
Observations	148	148
R^2	0.009	0.009
Adjusted R^2	0.002	0.002
Residual Std. Error (df = 146)	0.006	0.006
Note:		*p<0.1; **p<0.05; ***p<0.01

Table C.1.3 - Jensen's alpha for Closet Indexers

	CLOSET INDEXERS	
	Benchmark Adjusted Gross	Benchmark Adjusted Net
Alpha	0.001	−0.001
	t = 2.652***	t = −1.940*
Mkt-Rf	0.008	0.008
	t = 1.455	t = 1.475
Observations	148	148
R^2	0.014	0.015
Adjusted R^2	0.008	0.008
Residual Std. Error (df = 146)	0.003	0.003
Note:		*p<0.1; **p<0.05; ***p<0.01

Table C.1.4 - Jensen's alpha for Factor Bettors

	FACTOR BETTORS	
	Benchmark Adjusted Gross	Benchmark Adjusted Net
Alpha	0.001	−0.0001
	t = 2.112**	t = −0.138
Mkt-Rf	0.008	0.008
	t = 0.619	t = 0.623
Observations	148	148
R^2	0.003	0.003
Adjusted R^2	−0.004	−0.004
Residual Std. Error (df = 146)	0.008	0.008
Note:		*p<0.1; **p<0.05; ***p<0.01

Table C.2 – Carhart's Four-Factor alpha for Full Sample

	Abnormal Return	
	Benchmark Adjusted Gross	Benchmark Adjusted Net
Alpha	0.002	0.0004
	t = 5.250***	t = 1.129
Mkt-Rf	0.002	0.002
	t = 0.251	t = 0.243
SMB	−0.023	−0.023
	t = −1.238	t = −1.250
HML	−0.019	−0.019
	t = −0.855	t = −0.855
WML	−0.026	−0.026
	t = −2.530**	t = −2.521**
Observations	148	148
R^2	0.065	0.065
Adjusted R^2	0.039	0.039
Residual Std. Error (df = 143)	0.004	0.004
Note:		*p<0.1; **p<0.05; ***p<0.01

Table C.2.1 – Carhart's Four-Factor alpha for Stock Pickers

	STOCK PICKERS	
	Benchmark Adjusted Gross	Benchmark Adjusted Net
Alpha	0.001	0.0000
	t = 3.819***	t = 0.076
Mkt-Rf	−0.007	−0.007
	t = −0.945	t = −0.941
SMB	−0.009	−0.009
	t = −0.433	t = −0.442
HML	−0.014	−0.014
	t = −0.587	t = −0.564
WML	−0.025	−0.025
	t = −2.224**	t = −2.185**
Observations	148	148
R^2	0.036	0.035
Adjusted R^2	0.009	0.008
Residual Std. Error (df = 143)	0.004	0.004
Note:		*p<0.1; **p<0.05; ***p<0.01

Table C.2.2 – Carhart's Four-Factor alpha for Concentrated

	CONCENTRATED	
	Benchmark Adjusted Gross	Benchmark Adjusted Net
Alpha	0.003	0.001
	t = 5.199***	t = 2.671***
Mkt-Rf	0.005	0.005
	t = 0.454	t = 0.433
SMB	−0.040	−0.040
	t = −1.331	t = −1.354
HML	−0.032	−0.032
	t = −0.889	t = −0.905
WML	−0.029	−0.029
	t = −1.745*	t = −1.754*
Observations	148	148
R^2	0.044	0.045
Adjusted R^2	0.018	0.018
Residual Std. Error (df = 143)	0.006	0.006
Note:		*p<0.1; **p<0.05; ***p<0.01

Table C.2.3 – Carhart's Four-Factor alpha for Closet Indexers

	CLOSET INDEXERS	
	Benchmark Adjusted Gross	Benchmark Adjusted Net
Alpha	0.001	−0.0004
	t = 3.018***	t = −1.381
Mkt-Rf	0.005	0.005
	t = 0.760	t = 0.781
SMB	−0.017	−0.017
	t = −1.043	t = −1.033
HML	−0.007	−0.006
	t = −0.347	t = −0.303
WML	−0.014	−0.013
	t = −1.525	t = −1.499
Observations	148	148
R^2	0.039	0.039
Adjusted R^2	0.012	0.012
Residual Std. Error (df = 143)	0.003	0.003
Note:		*p<0.1; **p<0.05; ***p<0.01

Table C.2.3 – Carhart's Four-Factor alpha for Factor Bettors

	FACTOR BETTORS	
	Benchmark Adjusted Gross	Benchmark Adjusted Net
Alpha	0.001	−0.0000
	t = 2.094**	t = −0.039
Mkt-Rf	0.004	0.004
	t = 0.295	t = 0.297
SMB	−0.015	−0.015
	t = −0.403	t = −0.400
HML	0.017	0.017
	t = 0.371	t = 0.393
WML	−0.010	−0.010
	t = −0.504	t = −0.498
Observations	148	148
R^2	0.008	0.008
Adjusted R^2	−0.020	−0.020
Residual Std. Error (df = 143)	0.008	0.008
Note:		*p<0.1; **p<0.05; ***p<0.01

Table C.3 - Fama French Five-Factor alpha for Full Sample

	Abnormal Return	
	Benchmark Adjusted Gross	Benchmark Adjusted Net
Alpha	0.001	0.0000
	t = 3.818***	t = 0.070
Mkt-Rf	0.010	0.010
	t = 1.093	t = 1.079
SMB	−0.022	−0.022
	t = −1.088	t = −1.103
HML	0.007	0.007
	t = 0.259	t = 0.256
RMW	0.049	0.048
	t = 1.209	t = 1.197
CMA	−0.001	−0.001
	t = −0.034	t = −0.039
Observations	148	148
R^2	0.034	0.034
Adjusted R^2	0.0005	0.0003
Residual Std. Error (df = 142)	0.004	0.004
Note:		*p<0.1; **p<0.05; ***p<0.01

Table C 3.1 - Fama French Five-Factor alpha for Stock Pickers

	STOCK PICKERS	
	Benchmark Adjusted Gross	Benchmark Adjusted Net
Alpha	0.001	−0.0002
	t = 2.977***	t = −0.400
Mkt-Rf	−0.001	−0.002
	t = −0.152	t = −0.180
SMB	−0.013	−0.013
	t = −0.584	t = −0.608
HML	−0.005	−0.005
	t = −0.155	t = −0.155
RMW	0.001	−0.001
	t = 0.024	t = −0.028
CMA	0.001	0.001
	t = 0.036	t = 0.020
Observations	148	148
R^2	0.003	0.003
Adjusted R^2	−0.032	−0.032
Residual Std. Error (df = 142)	0.004	0.004
Note:		*p<0.1; **p<0.05; ***p<0.01

Table C 3.2 - Fama French Five-Factor alpha for Concentrated

	CONCENTRATED	
	Benchmark Adjusted Gross	Benchmark Adjusted Net
Alpha	0.003	0.001
	t = 4.330***	t = 2.008**
Mkt-Rf	0.016	0.016
	t = 1.184	t = 1.166
SMB	−0.041	−0.042
	t = −1.296	t = −1.319
HML	−0.036	−0.036
	t = −0.841	t = −0.849
RMW	−0.009	−0.009
	t = −0.145	t = −0.145
CMA	0.036	0.036
	t = 0.772	t = 0.767
Observations	148	148
R^2	0.029	0.029
Adjusted R^2	−0.005	−0.005
Residual Std. Error (df = 142)	0.006	0.006
Note:		*p<0.1; **p<0.05; ***p<0.01

Table C 3.3 - Fama French Five-Factor alpha for Closet Indexers

	Closet Indexers	
	Benchmark Adjusted Gross	Benchmark Adjusted Net
Alpha	0.001	−0.001
	t = 2.069**	t = −1.975*
Mkt-Rf	0.009	0.009
	t = 1.203	t = 1.195
SMB	−0.015	−0.015
	t = −0.869	t = −0.870
HML	0.012	0.013
	t = 0.530	t = 0.560
RMW	0.040	0.039
	t = 1.154	t = 1.125
CMA	−0.002	−0.003
	t = −0.094	t = −0.115
Observations	148	148
R^2	0.033	0.033
Adjusted R^2	−0.001	−0.001
Residual Std. Error (df = 142)	0.003	0.003
Note:		*p<0.1; **p<0.05; ***p<0.01

Table C 3.4 - Fama French Five-Factor alpha for Factor Bettors

	FACTOR BETTORS	
	Benchmark Adjusted Gross	Benchmark Adjusted Net
Alpha	0.001	−0.001
	t = 0.950	t = −1.050
Mkt-Rf	0.025	0.025
	t = 1.439	t = 1.441
SMB	0.012	0.012
	t = 0.296	t = 0.298
HML	0.039	0.039
	t = 0.731	t = 0.743
RMW	0.154	0.154
	t = 1.980**	t = 1.974*
CMA	0.062	0.062
	t = 1.064	t = 1.070
Observations	148	148
R^2	0.035	0.035
Adjusted R^2	0.001	0.001
Residual Std. Error (df = 142)	0.008	0.008

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

C.2 - Regression Outputs for Large Markets with High Correlation

Table C.4.1 – Jensen's alpha for Stock Pickers

	STOCK PICKERS			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.002	−0.0001	0.001	−0.001
	t = 2.625***	t = −0.132	t = 0.601	t = −0.975
Mkt-Rf	0.007	0.007	0.002	0.002
	t = 0.675	t = 0.674	t = 0.086	t = 0.083
Observations	148	148	148	148
R^2	0.003	0.003	0.0001	0.0000
Adjusted R^2	−0.004	−0.004	−0.007	−0.007
Residual Std. Error (df = 146)	0.007	0.007	0.011	0.011
Note:				*p<0.1; **p<0.05; ***p<0.01

Table C.4.2 – Jensen's alpha for Concentrated

	CONCENTRATED			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.001	−0.001	0.002	0.001
	t = 0.703	t = −0.498	t = 1.851*	t = 0.531
Mkt-Rf	0.020	0.021	0.017	0.017
	t = 0.802	t = 0.836	t = 0.779	t = 0.766
Observations	101	101	119	119
R^2	0.006	0.007	0.005	0.005
Adjusted R^2	−0.004	−0.003	−0.003	−0.004
Residual Std. Error	0.014 (df = 99)	0.014 (df = 99)	0.013 (df = 117)	0.013 (df = 117)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table C.4.3 – Jensen's alpha for Closet Indexers

	CLOSET INDEXERS			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	−0.0002	−0.002	0.0004	−0.001
	t = −0.677	t = −4.731***	t = 0.424	t = −1.264
Mkt-Rf	−0.003	−0.003	−0.011	−0.011
	t = −0.509	t = −0.503	t = −0.642	t = −0.632
Observations	148	148	148	148
R^2	0.002	0.002	0.003	0.003
Adjusted R^2	−0.005	−0.005	−0.004	−0.004
Residual Std. Error (df = 146)	0.004	0.004	0.010	0.010
Note:				*p<0.1; **p<0.05; ***p<0.01

Table C.4.4 – Jensen's alpha for Factor Bettors

	Factor Betters			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	−0.001	−0.002	0.001	−0.001
	t = −0.393	t = −1.070	t = 0.759	t = −0.608
Mkt-Rf	0.021	0.022	0.031	0.031
	t = 0.615	t = 0.624	t = 1.401	t = 1.392
Observations	87	87	111	111
R^2	0.004	0.005	0.018	0.017
Adjusted R^2	−0.007	−0.007	0.009	0.008
Residual Std. Error	0.016 (df = 85)	0.016 (df = 85)	0.013 (df = 109)	0.013 (df = 109)

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

Table C.5.1 – Carhart's Four Factor alpha for Stock Pickers

	STOCK PICKERS			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.002	0.0003	0.001	−0.0004
	t = 3.211***	t = 0.508	t = 1.099	t = −0.413
Mkt-Rf	−0.005	−0.005	−0.012	−0.012
	t = −0.383	t = −0.381	t = −0.590	t = −0.585
SMB	0.010	0.011	0.034	0.033
	t = 0.337	t = 0.348	t = 0.637	t = 0.621
HML	−0.007	−0.007	−0.029	−0.031
	t = −0.221	t = −0.217	t = −0.457	t = −0.477
WML	−0.044	−0.043	−0.065	−0.064
	t = −2.652***	t = −2.639***	t = −2.184**	t = −2.169**
Observations	148	148	148	148
R^2	0.052	0.052	0.034	0.034
Adjusted R^2	0.026	0.025	0.007	0.007
Residual Std. Error (df = 143)	0.007	0.007	0.011	0.011

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

Table C.5.2 – Carhart's Four Factor alpha for Concentrated

	CONCENTRATED			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.001	−0.001	0.003	0.001
	t = 0.514	t = −0.629	t = 2.229**	t = 0.969
Mkt-Rf	0.012	0.012	0.003	0.003
	t = 0.377	t = 0.381	t = 0.126	t = 0.106
SMB	0.011	0.010	0.096	0.096
	t = 0.138	t = 0.121	t = 1.277	t = 1.282
HML	0.076	0.080	−0.013	−0.013
	t = 0.923	t = 0.983	t = −0.154	t = −0.160
WML	0.027	0.028	−0.076	−0.077
	t = 0.649	t = 0.676	t = −2.096**	t = −2.123**
Observations	101	101	119	119
R^2	0.017	0.018	0.056	0.057
Adjusted R^2	−0.024	−0.022	0.023	0.024
Residual Std. Error	0.015 (df = 96)	0.014 (df = 96)	0.012 (df = 114)	0.012 (df = 114)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table C.5.3 – Carhart's Four Factor alpha for Closet Indexers

	CLOSET INDEXERS			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	−0.0001	−0.001	0.001	−0.0005
	t = −0.210	t = −4.158***	t = 1.145	t = −0.517
Mkt-Rf	−0.008	−0.008	−0.030	−0.030
	t = −1.079	t = −1.031	t = −1.683*	t = −1.667*
SMB	0.017	0.017	−0.109	−0.109
	t = 0.985	t = 0.949	t = −2.275**	t = −2.268**
HML	−0.006	−0.007	0.0004	0.0003
	t = −0.302	t = −0.356	t = 0.008	t = 0.005
WML	−0.020	−0.019	−0.063	−0.063
	t = −2.120**	t = −2.088**	t = −2.377**	t = −2.364**
Observations	148	148	148	148
R^2	0.039	0.038	0.082	0.081
Adjusted R^2	0.012	0.011	0.056	0.055
Residual Std. Error (df = 143)	0.004	0.004	0.010	0.010
Note:				*p<0.1; **p<0.05; ***p<0.01

Table C.5.4 – Carhart's Four Factor alpha for Factor Bettors

	Factor Betters			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	−0.0005	−0.002	0.001	−0.001
	t = −0.238	t = −0.877	t = 0.571	t = −0.744
Mkt-Rf	0.012	0.012	0.037	0.036
	t = 0.266	t = 0.284	t = 1.461	t = 1.455
SMB	−0.015	−0.016	0.007	0.007
	t = −0.150	t = −0.154	t = 0.095	t = 0.096
HML	0.012	0.010	0.031	0.031
	t = 0.128	t = 0.108	t = 0.393	t = 0.394
WML	−0.020	−0.020	0.024	0.024
	t = −0.358	t = −0.352	t = 0.634	t = 0.637
Observations	87	87	111	111
R^2	0.007	0.007	0.022	0.022
Adjusted R^2	−0.042	−0.042	−0.015	−0.015
Residual Std. Error	0.017 (df = 82)	0.017 (df = 82)	0.013 (df = 106)	0.013 (df = 106)

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

Table C.6.1 – Fama French Five- Factor alpha for Stock Pickers

	STOCK PICKERS			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.001	−0.0004	0.001	−0.0002
	t = 1.800*	t = −0.690	t = 1.241	t = −0.169
Mkt-Rf	−0.003	−0.003	−0.033	−0.032
	t = −0.224	t = −0.239	t = −1.300	t = −1.277
SMB	0.012	0.012	−0.009	−0.009
	t = 0.375	t = 0.378	t = −0.155	t = −0.158
HML	0.104	0.104	0.037	0.035
	t = 2.269**	t = 2.268**	t = 0.478	t = 0.453
RMW	0.138	0.136	−0.117	−0.115
	t = 2.131**	t = 2.112**	t = −1.027	t = −1.004
CMA	−0.063	−0.065	−0.178	−0.175
	t = −1.278	t = −1.309	t = −2.099**	t = −2.066**
Observations	148	148	148	148
R^2	0.055	0.055	0.034	0.033
Adjusted R^2	0.022	0.022	−0.0002	−0.001
Residual Std. Error (df = 142)	0.007	0.007	0.011	0.011

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

Table C.6.2 – Fama French Five- Factor alpha for Concentrated

	CONCENTRATED			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.0000	−0.002	0.003	0.001
	t = 0.022	t = −0.953	t = 2.011**	t = 0.816
Mkt-Rf	0.037	0.036	−0.005	−0.005
	t = 0.995	t = 0.981	t = −0.152	t = −0.154
SMB	0.032	0.027	0.060	0.061
	t = 0.380	t = 0.324	t = 0.753	t = 0.762
HML	0.035	0.029	0.020	0.020
	t = 0.293	t = 0.246	t = 0.211	t = 0.210
RMW	0.107	0.084	−0.135	−0.133
	t = 0.661	t = 0.524	t = −0.924	t = −0.914
CMA	0.183	0.179	−0.118	−0.116
	t = 1.457	t = 1.440	t = −1.107	t = −1.100
Observations	101	101	119	119
R^2	0.037	0.036	0.032	0.032
Adjusted R^2	−0.014	−0.014	−0.011	−0.011
Residual Std. Error	0.014 (df = 95)	0.014 (df = 95)	0.013 (df = 113)	0.013 (df = 113)

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

Table C.6.3 – Fama French Five- Factor alpha for Closet Indexers

	CLOSET INDEXERS			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	−0.0002	−0.002	0.001	−0.001
	t = −0.640	t = −4.251***	t = 0.614	t = −0.897
Mkt-Rf	−0.007	−0.007	−0.019	−0.018
	t = −0.927	t = −0.879	t = −0.816	t = −0.803
SMB	0.014	0.014	−0.121	−0.120
	t = 0.786	t = 0.755	t = −2.345**	t = −2.335**
HML	0.020	0.019	0.033	0.033
	t = 0.754	t = 0.702	t = 0.471	t = 0.467
RMW	0.012	0.012	−0.012	−0.011
	t = 0.323	t = 0.326	t = −0.114	t = −0.108
CMA	−0.029	−0.029	−0.004	−0.004
	t = −1.034	t = −1.005	t = −0.056	t = −0.051
Observations	148	148	148	148
R^2	0.017	0.016	0.046	0.046
Adjusted R^2	−0.017	−0.018	0.013	0.012
Residual Std. Error (df = 142)	0.004	0.004	0.010	0.010

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

Table C.6.4 – Fama French Five- Factor alpha for Factor Bettors

	Factor Betters			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	−0.001	−0.002	0.001	−0.001
	t = −0.582	t = −1.193	t = 0.431	t = −0.766
Mkt-Rf	0.014	0.015	0.044	0.044
	t = 0.327	t = 0.345	t = 1.348	t = 1.343
SMB	0.018	0.017	0.026	0.026
	t = 0.167	t = 0.164	t = 0.331	t = 0.331
HML	0.155	0.153	0.005	0.005
	t = 1.106	t = 1.094	t = 0.056	t = 0.053
RMW	0.190	0.191	0.044	0.043
	t = 1.018	t = 1.023	t = 0.289	t = 0.285
CMA	−0.111	−0.110	0.061	0.061
	t = −0.638	t = −0.635	t = 0.550	t = 0.553
Observations	87	87	111	111
R^2	0.025	0.025	0.022	0.022
Adjusted R^2	−0.035	−0.035	−0.025	−0.025
Residual Std. Error	0.017 (df = 81)	0.017 (df = 81)	0.013 (df = 105)	0.013 (df = 105)

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

C.3 - REGRESSION OUTPUTS FOR LARGE MARKETS WITH LOW CORRELATION

Table C.7.1 – Jensen's alpha for Stock Pickers

	STOCK PICKERS	
	Global(Gross)	Global(Net)
Alpha	0.001	−0.001
	t = 1.325	t = −1.351
Mkt-Rf	−0.003	−0.003
	t = −0.275	t = −0.288
Observations	148	148
R^2	0.001	0.001
Adjusted R^2	−0.006	−0.006
Residual Std. Error (df = 146)	0.006	0.006
Note:	*p<0.1; **p<0.05; ***p<0.01	
	Only global funds in this category	

Table C.7.2 – Jensen's alpha for Concentrated

	CONCENTRATED	
	Global(Gross)	Global(Net)
Alpha	0.001	−0.001
	t = 1.325	t = −0.975
Mkt-Rf	−0.003	0.002
	t = −0.275	t = 0.083
Observations	148	148
R^2	0.001	0.0000
Adjusted R^2	−0.006	−0.007
Residual Std. Error (df = 146)	0.006	0.011
Note:	*p<0.1; **p<0.05; ***p<0.01	
	Only global funds in this category	

Table C.7.3 – Jensen's alpha for Closet Indexers

	CLOSET INDEXERS	
	Global(Gross)	Global(Net)
Alpha	−0.0004	−0.002
	t = −1.221	t = −5.252***
Mkt-Rf	0.003	0.002
	t = 0.349	t = 0.318
Observations	146	146
R^2	0.001	0.001
Adjusted R^2	−0.006	−0.006
Residual Std. Error (df = 144)	0.004	0.004
Note:	*p<0.1; **p<0.05; ***p<0.01	
	Only global funds in this category	

Table C.7.4 – Jensen's alpha for Factor Bettors

	FACTOR BETTERS	
	Global(Gross)	Global(Net)
Alpha	−0.0005	−0.002
	t = −0.531	t = −2.321**
Mkt-Rf	0.018	0.018
	t = 1.026	t = 1.039
Observations	144	144
R^2	0.007	0.008
Adjusted R^2	0.0004	0.001
Residual Std. Error (df = 142)	0.010	0.010
Note:		*p<0.1; **p<0.05; ***p<0.01
		Only global funds in this category

Table C.8.1 – Carhart's Four Factor alpha for Stock Pickers

	STOCK PICKERS	
	Global(Gross)	Global(Net)
Alpha	0.001	−0.0004
	t = 1.835*	t = −0.726
Mkt-Rf	−0.007	−0.007
	t = −0.678	t = −0.688
SMB	−0.012	−0.012
	t = −0.456	t = −0.464
HML	−0.039	−0.038
	t = −1.215	t = −1.199
WML	−0.023	−0.023
	t = −1.559	t = −1.543
Observations	148	148
R^2	0.025	0.024
Adjusted R^2	−0.003	−0.003
Residual Std. Error (df = 143)	0.006	0.006
Note:		*p<0.1; **p<0.05; ***p<0.01
		Only global funds in this category

Table C.8.2 – Carhart's Four Factor alpha for Concentrated

	CONCENTRATED	
	Global(Gross)	Global(Net)
Alpha	0.003	0.002
	t = 4.212***	t = 2.389**
Mkt-Rf	0.005	0.005
	t = 0.347	t = 0.335
SMB	−0.083	−0.083
	t = −2.159**	t = −2.179**
HML	−0.032	−0.033
	t = −0.707	t = −0.722
WML	−0.040	−0.040
	t = −1.880*	t = −1.883*
Observations	148	148
R^2	0.067	0.067
Adjusted R^2	0.041	0.041
Residual Std. Error (df = 143)	0.008	0.008
Note:	*p<0.1; **p<0.05; ***p<0.01	
	Only global funds in this category	

Table C.8.3 – Carhart's Four Factor alpha for Closet Indexers

	CLOSET INDEXERS	
	Global(Gross)	Global(Net)
Alpha	−0.0003	−0.002
	t = −0.660	t = −4.498***
Mkt-Rf	0.001	0.001
	t = 0.111	t = 0.078
SMB	−0.033	−0.034
	t = −1.608	t = −1.629
HML	−0.030	−0.030
	t = −1.200	t = −1.198
WML	−0.010	−0.010
	t = −0.837	t = −0.842
Observations	146	146
R^2	0.029	0.029
Adjusted R^2	0.001	0.002
Residual Std. Error (df = 141)	0.004	0.004
Note:	*p<0.1; **p<0.05; ***p<0.01	
	Only global funds in this category	

Table C.8.4 – Carhart's Four Factor alpha for Factor Bettors

	FACTOR BETTERS	
	Global(Gross)	Global(Net)
Alpha	−0.001	−0.002
	t = −0.732	t = −2.431**
Mkt-Rf	0.018	0.018
	t = 0.959	t = 0.972
SMB	−0.010	−0.010
	t = −0.187	t = −0.201
HML	0.057	0.057
	t = 0.926	t = 0.938
WML	0.013	0.014
	t = 0.478	t = 0.489
Observations	144	144
R^2	0.015	0.015
Adjusted R^2	−0.013	−0.013
Residual Std. Error (df = 139)	0.011	0.011
Note:	*p<0.1; **p<0.05; ***p<0.01	
	Only global funds in this category	

Table C.9.1 – Fama French Five-Factor alpha for Stock Pickers

	STOCK PICKERS	
	Global(Gross)	Global(Net)
Alpha	0.001	−0.0003
	t = 1.808*	t = −0.543
Mkt-Rf	−0.006	−0.006
	t = −0.473	t = −0.497
SMB	−0.026	−0.026
	t = −0.914	t = −0.930
HML	−0.048	−0.047
	t = −1.243	t = −1.236
RMW	−0.069	−0.070
	t = −1.212	t = −1.236
CMA	−0.003	−0.003
	t = −0.068	t = −0.079
Observations	148	148
R^2	0.019	0.020
Adjusted R^2	−0.015	−0.015
Residual Std. Error (df = 142)	0.006	0.006
Note:	*p<0.1; **p<0.05; ***p<0.01	
	Only global funds in this category	

Table C.9.2 – Fama French Five-Factor alpha for Concentrated

	CONCENTRATED	
	Global(Gross)	Global(Net)
Alpha	0.003	0.002
	t = 4.153***	t = 2.446**
Mkt-Rf	0.014	0.014
	t = 0.778	t = 0.768
SMB	−0.102	−0.102
	t = −2.550**	t = −2.568**
HML	−0.084	−0.084
	t = −1.552	t = −1.561
RMW	−0.169	−0.169
	t = −2.117**	t = −2.115**
CMA	0.059	0.059
	t = 0.985	t = 0.983
Observations	148	148
R^2	0.087	0.087
Adjusted R^2	0.055	0.055
Residual Std. Error (df = 142)	0.008	0.008
Note:	*p<0.1; **p<0.05; ***p<0.01	
	Only global funds in this category	

Table C.9.3 – Fama French Five-Factor alpha for Closet Indexers

	CLOSET INDEXERS	
	Global(Gross)	Global(Net)
Alpha	−0.0004	−0.002
	t = −0.907	t = −4.482***
Mkt-Rf	0.006	0.005
	t = 0.567	t = 0.532
SMB	−0.034	−0.035
	t = −1.576	t = −1.602
HML	−0.028	−0.028
	t = −0.932	t = −0.930
RMW	0.008	0.007
	t = 0.182	t = 0.165
CMA	0.016	0.016
	t = 0.484	t = 0.474
Observations	146	146
R^2	0.028	0.029
Adjusted R^2	−0.006	−0.006
Residual Std. Error (df = 140)	0.004	0.004
Note:	*p<0.1; **p<0.05; ***p<0.01	
	Only global funds in this category	

Table C.9.4 – Fama French Five-Factor alpha for Factor Bettors

	FACTOR BETTERS	
	Global(Gross)	Global(Net)
Alpha	−0.001	−0.002
	t = −0.532	t = −2.098**
Mkt-Rf	0.018	0.018
	t = 0.741	t = 0.738
SMB	−0.008	−0.008
	t = −0.138	t = −0.152
HML	0.038	0.040
	t = 0.526	t = 0.550
RMW	−0.020	−0.019
	t = −0.177	t = −0.169
CMA	0.022	0.020
	t = 0.277	t = 0.255
Observations	144	144
R^2	0.014	0.015
Adjusted R^2	−0.021	−0.021
Residual Std. Error (df = 138)	0.011	0.011
Note:	*p<0.1; **p<0.05; ***p<0.01	
	Only global funds in this category	

C.4 - Regression Outputs for Small Markets with High Correlation

Table C.10.1 – Jensen's alpha for Stock Pickers

	STOCK PICKERS			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.003	0.001	0.002	−0.0003
	t = 2.142**	t = 0.647	t = 0.732	t = −0.104
Mkt-Rf	0.021	0.021	0.018	0.017
	t = 1.005	t = 0.995	t = 0.370	t = 0.354
Observations	148	148	142	142
R^2	0.007	0.007	0.001	0.001
Adjusted R^2	0.0001	−0.0001	−0.006	−0.006
Residual Std. Error	0.014 (df = 146)	0.014 (df = 146)	0.028 (df = 140)	0.028 (df = 140)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table C.10.2 – Jensen's alpha for Concentrated

	CONCENTRATED			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.003	0.002	0.005	0.003
	t = 2.659***	t = 1.473	t = 2.016**	t = 1.243
Mkt-Rf	−0.013	−0.014	0.062	0.063
	t = −0.561	t = −0.596	t = 1.274	t = 1.288
Observations	148	148	138	138
R^2	0.002	0.002	0.012	0.012
Adjusted R^2	−0.005	−0.004	0.005	0.005
Residual Std. Error	0.016 (df = 146)	0.016 (df = 146)	0.029 (df = 136)	0.029 (df = 136)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table C.10.3 – Jensen's alpha for Closet Indexers

	CLOSET INDEXERS			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.001	−0.0001	0.002	−0.0001
	t = 2.146**	t = −0.097	t = 1.152	t = −0.037
Mkt-Rf	0.004	0.004	0.024	0.024
	t = 0.346	t = 0.366	t = 0.789	t = 0.771
Observations	148	148	138	138
R^2	0.001	0.001	0.005	0.004
Adjusted R^2	−0.006	−0.006	−0.003	−0.003
Residual Std. Error	0.008 (df = 146)	0.008 (df = 146)	0.018 (df = 136)	0.018 (df = 136)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table C.10.4 – Jensen's alpha for Factor Bettors

	FACTOR BETTERS			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.002	0.001	0.004	0.002
	t = 2.001**	t = 0.615	t = 2.173**	t = 1.109
Mkt-Rf	−0.008	−0.008	0.023	0.022
	t = −0.483	t = −0.501	t = 0.621	t = 0.608
Observations	134	134	139	139
R^2	0.002	0.002	0.003	0.003
Adjusted R^2	−0.006	−0.006	−0.004	−0.005
Residual Std. Error	0.010 (df = 132)	0.010 (df = 132)	0.021 (df = 137)	0.021 (df = 137)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table C.11.1 – Carhart Four-Factor alpha for Stock Pickers

	STOCK PICKERS			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.003	0.001	0.001	−0.001
	t = 2.127**	t = 0.700	t = 0.244	t = −0.559
Mkt-Rf	0.010	0.010	0.040	0.039
	t = 0.369	t = 0.377	t = 0.787	t = 0.767
SMB	−0.052	−0.053	−0.178	−0.179
	t = −0.825	t = −0.846	t = −1.284	t = −1.295
HML	0.055	0.052	0.168	0.166
	t = 0.816	t = 0.766	t = 1.032	t = 1.020
WML	0.003	0.002	0.141	0.139
	t = 0.084	t = 0.055	t = 1.874*	t = 1.859*
Observations	148	148	142	142
R^2	0.017	0.016	0.041	0.041
Adjusted R^2	−0.011	−0.011	0.013	0.013
Residual Std. Error	0.014 (df = 143)	0.014 (df = 143)	0.028 (df = 137)	0.028 (df = 137)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table C.11.2 – Carhart Four-Factor alpha for Concentrated

	CONCENTRATED			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.004	0.002	0.005	0.003
	t = 2.851***	t = 1.712*	t = 1.784*	t = 1.045
Mkt-Rf	−0.030	−0.031	0.064	0.065
	t = −1.021	t = −1.052	t = 1.191	t = 1.206
SMB	−0.022	−0.022	−0.074	−0.072
	t = −0.308	t = −0.311	t = −0.511	t = −0.504
HML	0.021	0.021	0.105	0.108
	t = 0.271	t = 0.279	t = 0.614	t = 0.637
WML	−0.039	−0.038	0.033	0.034
	t = −1.040	t = −1.037	t = 0.412	t = 0.423
Observations	148	148	138	138
R^2	0.013	0.013	0.018	0.018
Adjusted R^2	−0.015	−0.015	−0.012	−0.011
Residual Std. Error	0.016 (df = 143)	0.016 (df = 143)	0.029 (df = 133)	0.029 (df = 133)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table C.11.3 – Carhart Four-Factor alpha for Closet Indexers

	CLOSET INDEXERS			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.002	0.0002	0.002	0.0002
	t = 2.471**	t = 0.292	t = 1.227	t = 0.106
Mkt-Rf	0.0002	0.0003	0.015	0.014
	t = 0.014	t = 0.019	t = 0.442	t = 0.425
SMB	0.009	0.010	−0.064	−0.065
	t = 0.272	t = 0.303	t = −0.687	t = −0.700
HML	−0.028	−0.026	0.029	0.027
	t = −0.764	t = −0.711	t = 0.264	t = 0.253
WML	−0.031	−0.030	−0.023	−0.023
	t = −1.737*	t = −1.689*	t = −0.468	t = −0.470
Observations	148	148	138	138
R^2	0.023	0.022	0.012	0.012
Adjusted R^2	−0.005	−0.006	−0.018	−0.018
Residual Std. Error	0.008 (df = 143)	0.008 (df = 143)	0.019 (df = 133)	0.019 (df = 133)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table C.11.4 – Carhart Four-Factor alpha for Factor Bettors

	FACTOR BETTERS			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.002	0.001	0.004	0.002
	t = 2.295**	t = 0.959	t = 2.037**	t = 1.028
Mkt-Rf	−0.019	−0.019	0.016	0.016
	t = −0.976	t = −0.985	t = 0.415	t = 0.404
SMB	−0.055	−0.057	−0.113	−0.114
	t = −1.157	t = −1.189	t = −1.042	t = −1.058
HML	0.001	−0.001	0.051	0.050
	t = 0.030	t = −0.015	t = 0.394	t = 0.385
WML	−0.031	−0.032	0.003	0.004
	t = −1.227	t = −1.268	t = 0.056	t = 0.060
Observations	134	134	139	139
R^2	0.023	0.025	0.014	0.014
Adjusted R^2	−0.007	−0.006	−0.016	−0.016
Residual Std. Error	0.010 (df = 129)	0.010 (df = 129)	0.021 (df = 134)	0.021 (df = 134)

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

Table C.12.1 – Fama French Five-Factor alpha for Stock Pickers

	STOCK PICKERS			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.002	−0.0002	−0.001	−0.003
	t = 1.199	t = −0.133	t = −0.468	t = −1.223
Mkt-Rf	0.014	0.014	0.111	0.110
	t = 0.502	t = 0.509	t = 1.771*	t = 1.748*
SMB	−0.034	−0.036	−0.030	−0.032
	t = −0.533	t = −0.559	t = −0.207	t = −0.222
HML	0.189	0.183	0.139	0.138
	t = 2.062**	t = 2.005**	t = 0.722	t = 0.719
RMW	0.288	0.281	0.662	0.659
	t = 2.234**	t = 2.191**	t = 2.325**	t = 2.317**
CMA	0.023	0.021	0.418	0.414
	t = 0.229	t = 0.219	t = 1.974*	t = 1.960*
Observations	148	148	142	142
R^2	0.050	0.049	0.067	0.067
Adjusted R^2	0.017	0.015	0.033	0.032
Residual Std. Error	0.014 (df = 142)	0.014 (df = 142)	0.028 (df = 136)	0.028 (df = 136)

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

Table C.12.2 – Fama French Five-Factor alpha for Concentrated

	CONCENTRATED			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.002	0.001	0.002	0.0002
	t = 1.625	t = 0.557	t = 0.770	t = 0.073
Mkt-Rf	−0.027	−0.028	0.134	0.134
	t = −0.859	t = −0.895	t = 2.007**	t = 2.006**
SMB	−0.009	−0.009	0.050	0.051
	t = −0.124	t = −0.132	t = 0.338	t = 0.345
HML	0.243	0.242	0.195	0.202
	t = 2.389**	t = 2.383**	t = 0.971	t = 1.004
RMW	0.369	0.365	0.702	0.705
	t = 2.579**	t = 2.558**	t = 2.373**	t = 2.385**
CMA	−0.061	−0.061	0.239	0.233
	t = −0.554	t = −0.564	t = 1.051	t = 1.029
Observations	148	148	138	138
R^2	0.057	0.057	0.058	0.059
Adjusted R^2	0.024	0.024	0.022	0.023
Residual Std. Error	0.016 (df = 142)	0.015 (df = 142)	0.029 (df = 132)	0.029 (df = 132)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table C.12.3 – Fama French Five-Factor alpha for Closet Indexers

	CLOSET INDEXERS			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.001	−0.0004	0.001	−0.001
	t = 1.421	t = −0.564	t = 0.290	t = −0.752
Mkt-Rf	0.005	0.004	0.056	0.056
	t = 0.293	t = 0.273	t = 1.350	t = 1.337
SMB	0.012	0.013	−0.008	−0.009
	t = 0.345	t = 0.365	t = −0.077	t = −0.090
HML	0.046	0.047	0.080	0.078
	t = 0.910	t = 0.927	t = 0.624	t = 0.610
RMW	0.103	0.100	0.317	0.315
	t = 1.448	t = 1.416	t = 1.673*	t = 1.666*
CMA	−0.022	−0.023	0.121	0.122
	t = −0.404	t = −0.434	t = 0.849	t = 0.853
Observations	148	148	138	138
R^2	0.020	0.019	0.032	0.031
Adjusted R^2	−0.015	−0.015	−0.005	−0.005
Residual Std. Error	0.008 (df = 142)	0.008 (df = 142)	0.018 (df = 132)	0.018 (df = 132)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table C.12.4 – Fama French Five-Factor alpha for Factor Bettors

	FACTOR BETTERS			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.002	0.001	0.003	0.001
	t = 2.255**	t = 1.028	t = 1.413	t = 0.470
Mkt-Rf	−0.028	−0.029	0.041	0.041
	t = −1.324	t = −1.344	t = 0.828	t = 0.827
SMB	−0.068	−0.070	−0.070	−0.071
	t = −1.378	t = −1.412	t = −0.612	t = −0.624
HML	0.055	0.055	0.098	0.096
	t = 0.788	t = 0.794	t = 0.638	t = 0.625
RMW	−0.018	−0.016	0.271	0.271
	t = −0.180	t = −0.165	t = 1.175	t = 1.177
CMA	−0.116	−0.120	0.079	0.081
	t = −1.539	t = −1.588	t = 0.475	t = 0.490
Observations	134	134	139	139
R^2	0.032	0.033	0.023	0.023
Adjusted R^2	−0.006	−0.005	−0.013	−0.013
Residual Std. Error	0.010 (df = 128)	0.010 (df = 128)	0.021 (df = 133)	0.021 (df = 133)
Note:				*p<0.1; **p<0.05; ***p<0.01

C.5 - Regression Outputs for Small Markets with Low Correlation

Table C.13.1 – Jensen's alpha for Stock Pickers

	STOCK PICKERS			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.0004	−0.001	0.003	0.002
	t = 0.348	t = −0.899	t = 2.617***	t = 1.331
Mkt-Rf	0.058	0.058	−0.008	−0.009
	t = 2.961***	t = 2.940***	t = −0.339	t = −0.344
Observations	126	126	148	148
R^2	0.066	0.065	0.001	0.001
Adjusted R^2	0.058	0.058	−0.006	−0.006
Residual Std. Error	0.012 (df = 124)	0.012 (df = 124)	0.015 (df = 146)	0.015 (df = 146)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table C.13.2 – Jensen's alpha for Concentrated

	CONCENTRATED			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.003	0.001	0.003	0.002
	t = 2.036**	t = 0.822	t = 2.226**	t = 1.066
Mkt-Rf	0.038	0.039	−0.010	−0.010
	t = 1.642	t = 1.683*	t = −0.322	t = −0.316
Observations	148	148	148	148
R^2	0.018	0.019	0.001	0.001
Adjusted R^2	0.011	0.012	−0.006	−0.006
Residual Std. Error (df = 146)	0.016	0.016	0.018	0.018
Note:				*p<0.1; **p<0.05; ***p<0.01

Table C.13.3 – Jensen's alpha for Closet Indexers

	CLOSET INDEXERS			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.001	−0.0001	0.002	0.0002
	t = 2.362**	t = −0.178	t = 2.403**	t = 0.228
Mkt-Rf	0.021	0.021	−0.010	−0.010
	t = 2.811***	t = 2.817***	t = −0.714	t = −0.714
Observations	148	148	148	148
R^2	0.051	0.052	0.003	0.003
Adjusted R^2	0.045	0.045	−0.003	−0.003
Residual Std. Error (df = 146)	0.005	0.005	0.009	0.009
Note:				*p<0.1; **p<0.05; ***p<0.01

Table C.13.4 – Jensen's alpha for Factor Bettors

	FACTOR BETTERS			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.001	−0.0001	0.001	−0.001
	t = 1.027	t = −0.178	t = 0.713	t = −0.670
Mkt-Rf	0.039	0.021	−0.013	−0.013
	t = 2.098**	t = 2.817***	t = −0.593	t = −0.597
Observations	148	148	105	105
R^2	0.029	0.052	0.003	0.003
Adjusted R^2	0.023	0.045	−0.006	−0.006
Residual Std. Error	0.013 (df = 146)	0.005 (df = 146)	0.012 (df = 103)	0.012 (df = 103)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table C.14.1 – Carhart Four-Factor alpha for Stock Pickers

	STOCK PICKERS			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.0004	−0.001	0.004	0.002
	t = 0.307	t = −0.893	t = 2.674***	t = 1.457
Mkt-Rf	0.040	0.040	−0.003	−0.003
	t = 1.586	t = 1.582	t = −0.113	t = −0.118
SMB	−0.029	−0.029	0.021	0.020
	t = −0.493	t = −0.500	t = 0.287	t = 0.281
HML	0.116	0.115	−0.115	−0.117
	t = 1.911*	t = 1.883*	t = −1.342	t = −1.361
WML	0.031	0.031	−0.003	−0.004
	t = 1.043	t = 1.037	t = −0.085	t = −0.091
Observations	126	126	148	148
R^2	0.098	0.096	0.015	0.015
Adjusted R^2	0.068	0.066	−0.012	−0.012
Residual Std. Error	0.012 (df = 121)	0.012 (df = 121)	0.015 (df = 143)	0.015 (df = 143)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table C.14.2 – Carhart Four-Factor alpha for Concentrated

	CONCENTRATED			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.003	0.001	0.004	0.002
	t = 2.167**	t = 0.993	t = 2.433**	t = 1.302
Mkt-Rf	0.005	0.005	0.004	0.005
	t = 0.170	t = 0.190	t = 0.134	t = 0.144
SMB	0.020	0.021	0.098	0.098
	t = 0.290	t = 0.307	t = 1.142	t = 1.146
HML	0.118	0.119	−0.248	−0.246
	t = 1.574	t = 1.597	t = −2.416**	t = −2.404**
WML	−0.026	−0.026	−0.004	−0.004
	t = −0.698	t = −0.700	t = −0.089	t = −0.075
Observations	148	148	148	148
R^2	0.044	0.046	0.056	0.056
Adjusted R^2	0.017	0.019	0.029	0.029
Residual Std. Error (df = 143)	0.016	0.016	0.018	0.018
Note:				*p<0.1; **p<0.05; ***p<0.01

Table C.14.3 – Carhart Four-Factor alpha for Closet Indexers

	CLOSET INDEXERS			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.001	−0.0001	0.002	0.001
	t = 2.248**	t = −0.202	t = 3.145***	t = 0.953
Mkt-Rf	0.013	0.013	−0.002	−0.002
	t = 1.356	t = 1.348	t = −0.154	t = −0.161
SMB	0.005	0.005	−0.001	0.0000
	t = 0.204	t = 0.215	t = −0.019	t = 0.0000
HML	0.045	0.045	−0.211	−0.211
	t = 1.819*	t = 1.830*	t = −4.475***	t = −4.469***
WML	0.003	0.003	−0.008	−0.009
	t = 0.261	t = 0.245	t = −0.375	t = −0.396
Observations	148	148	148	148
R^2	0.073	0.074	0.129	0.129
Adjusted R^2	0.047	0.048	0.105	0.104
Residual Std. Error (df = 143)	0.005	0.005	0.008	0.008

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

Table C.14.4 – Carhart Four-Factor alpha for Factor Bettors

	FACTOR BETTERS			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.001	−0.0001	0.001	−0.001
	t = 1.016	t = −0.202	t = 0.758	t = −0.602
Mkt-Rf	0.022	0.013	−0.008	−0.008
	t = 0.966	t = 1.348	t = −0.318	t = −0.320
SMB	0.022	0.005	−0.075	−0.075
	t = 0.398	t = 0.215	t = −1.111	t = −1.106
HML	0.072	0.045	−0.141	−0.140
	t = 1.207	t = 1.830*	t = −1.817*	t = −1.806*
WML	−0.003	0.003	0.003	0.003
	t = −0.115	t = 0.245	t = 0.077	t = 0.082
Observations	148	148	105	105
R^2	0.041	0.074	0.042	0.041
Adjusted R^2	0.014	0.048	0.003	0.003
Residual Std. Error	0.013 (df = 143)	0.005 (df = 143)	0.012 (df = 100)	0.012 (df = 100)

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

Table C.15.1 – Fama French Five-Factor alpha for Stock Pickers

	STOCK PICKERS			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.0003	−0.001	0.004	0.002
	t = 0.256	t = −0.854	t = 2.559**	t = 1.405
Mkt-Rf	0.039	0.039	0.026	0.026
	t = 1.475	t = 1.485	t = 0.784	t = 0.782
SMB	−0.021	−0.021	0.027	0.026
	t = −0.339	t = −0.338	t = 0.358	t = 0.352
HML	0.115	0.114	−0.262	−0.263
	t = 1.364	t = 1.353	t = −2.600**	t = −2.616***
RMW	0.057	0.060	−0.167	−0.166
	t = 0.467	t = 0.492	t = −1.119	t = −1.118
CMA	0.050	0.053	0.220	0.220
	t = 0.561	t = 0.587	t = 1.983**	t = 1.985**
Observations	126	126	148	148
R^2	0.093	0.092	0.058	0.058
Adjusted R^2	0.055	0.054	0.024	0.025
Residual Std. Error	0.012 (df = 120)	0.012 (df = 120)	0.015 (df = 142)	0.015 (df = 142)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table C.15.2 – Fama French Five-Factor alpha for Concentrated

	CONCENTRATED			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.002	0.0005	0.004	0.002
	t = 1.406	t = 0.318	t = 2.150**	t = 1.105
Mkt-Rf	0.029	0.029	0.023	0.023
	t = 0.927	t = 0.934	t = 0.586	t = 0.589
SMB	0.035	0.036	0.108	0.108
	t = 0.489	t = 0.504	t = 1.191	t = 1.194
HML	0.126	0.129	−0.322	−0.321
	t = 1.230	t = 1.257	t = −2.624***	t = −2.621***
RMW	0.091	0.091	−0.046	−0.048
	t = 0.631	t = 0.632	t = −0.255	t = −0.263
CMA	0.140	0.137	0.118	0.117
	t = 1.270	t = 1.244	t = 0.869	t = 0.870
Observations	148	148	148	148
R^2	0.052	0.053	0.063	0.062
Adjusted R^2	0.019	0.020	0.030	0.029
Residual Std. Error (df = 142)	0.016	0.016	0.018	0.018
Note:				*p<0.1; **p<0.05; ***p<0.01

Table C.15.3 – Fama French Five-Factor alpha for Closet Indexers

	CLOSET INDEXERS			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.001	−0.0004	0.003	0.001
	t = 1.394	t = −0.900	t = 3.378***	t = 1.306
Mkt-Rf	0.017	0.017	0.002	0.002
	t = 1.661*	t = 1.655	t = 0.102	t = 0.098
SMB	0.013	0.013	−0.017	−0.017
	t = 0.554	t = 0.564	t = −0.425	t = −0.409
HML	0.070	0.071	−0.280	−0.279
	t = 2.100**	t = 2.114**	t = −5.031***	t = −5.021***
RMW	0.079	0.079	−0.151	−0.151
	t = 1.682*	t = 1.683*	t = −1.838*	t = −1.838*
CMA	0.031	0.031	0.063	0.062
	t = 0.874	t = 0.866	t = 1.024	t = 1.017
Observations	148	148	148	148
R^2	0.093	0.093	0.161	0.160
Adjusted R^2	0.061	0.062	0.131	0.131
Residual Std. Error (df = 142)	0.005	0.005	0.008	0.008
Note:				*p<0.1; **p<0.05; ***p<0.01

Table C.15.4 – Fama French Five-Factor alpha for Factor Bettors

	FACTOR BETTERS			
	Europe(Gross)	Europe(Net)	Global(Gross)	Global(Net)
Alpha	0.0000	−0.0004	0.002	−0.0000
	t = 0.035	t = −0.900	t = 1.254	t = −0.011
Mkt-Rf	0.042	0.017	−0.012	−0.012
	t = 1.692*	t = 1.655	t = −0.396	t = −0.393
SMB	0.050	0.013	−0.099	−0.098
	t = 0.881	t = 0.564	t = −1.355	t = −1.347
HML	0.121	0.071	−0.217	−0.216
	t = 1.487	t = 2.114**	t = −2.331**	t = −2.324**
RMW	0.194	0.079	−0.231	−0.230
	t = 1.693*	t = 1.683*	t = −1.645	t = −1.638
CMA	0.133	0.031	0.040	0.041
	t = 1.517	t = 0.866	t = 0.391	t = 0.398
Observations	148	148	105	105
R^2	0.070	0.093	0.071	0.071
Adjusted R^2	0.037	0.062	0.025	0.024
Residual Std. Error	0.012 (df = 142)	0.005 (df = 142)	0.012 (df = 99)	0.012 (df = 99)
Note:				*p<0.1; **p<0.05; ***p<0.01

C.6 - Regression Outputs for Large Markets on Persistence by 2004 and 2009 AS Quartiles

Table C.16.1 – Fama French Five-Factor alpha for AS Quartiles from 2004

	AS QUARTILES FROM 2004			
	Highest	2nd	3rd	Lowest
Alpha	0.005	0.001	0.001	−0.0003
	t = 2.455**	t = 1.237	t = 0.589	t = −0.625
Mkt-Rf	0.046	0.022	0.001	−0.006
	t = 0.806	t = 0.687	t = 0.043	t = −0.486
SMB	−0.088	0.031	−0.003	−0.043
	t = −0.752	t = 0.476	t = −0.047	t = −1.569
HML	0.140	−0.144	−0.119	−0.019
	t = 0.877	t = −1.623	t = −1.524	t = −0.509
RMW	−0.063	−0.180	−0.175	−0.098
	t = −0.248	t = −1.266	t = −1.399	t = −1.648
CMA	−0.012	0.103	0.050	−0.033
	t = −0.067	t = 1.056	t = 0.585	t = −0.817
Observations	60	60	60	60
R^2	0.090	0.076	0.072	0.077
Adjusted R^2	0.006	−0.009	−0.014	−0.008
Residual Std. Error (df = 54)	0.015	0.008	0.007	0.004

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

Table C.16.2 – Fama French Five-Factor alpha for AS Quartiles from 2009

	AS QUARTILES FROM 2009			
	Highest	2nd	3rd	Lowest
Alpha	0.002	0.002	0.0003	−0.001
	t = 1.602	t = 2.103**	t = 0.611	t = −2.033**
Mkt-Rf	−0.009	0.012	0.021	0.020
	t = −0.239	t = 0.555	t = 1.469	t = 1.624
SMB	−0.109	−0.023	−0.011	−0.014
	t = −1.195	t = −0.407	t = −0.302	t = −0.452
HML	−0.024	0.065	0.047	0.033
	t = −0.201	t = 0.897	t = 0.981	t = 0.830
RMW	−0.038	0.060	0.062	0.038
	t = −0.220	t = 0.568	t = 0.891	t = 0.647
CMA	−0.059	−0.042	0.017	0.046
	t = −0.383	t = −0.448	t = 0.277	t = 0.892
Observations	59	59	59	59
R^2	0.038	0.038	0.107	0.159
Adjusted R^2	−0.053	−0.053	0.023	0.079
Residual Std. Error (df = 53)	0.009	0.005	0.003	0.003

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

C.7 - Regression Outputs for Small Markets on Persistence by 2004 and 2009 AS Quartiles

Table C.17.1 – Fama French Five-Factor alpha for AS Quartiles from 2004

	AS QUARTILES FROM 2004			
	Highest	2nd	3rd	Lowest
Alpha	0.0003	0.001	−0.0002	−0.001
	t = 0.183	t = 0.970	t = −0.192	t = −1.399
Mkt-Rf	0.014	−0.025	0.024	0.005
	t = 0.388	t = −1.026	t = 1.002	t = 0.394
SMB	−0.005	−0.041	−0.022	−0.027
	t = −0.064	t = −0.851	t = −0.482	t = −1.019
HML	0.145	0.184	0.104	0.043
	t = 1.222	t = 2.314**	t = 1.368	t = 0.988
RMW	0.305	0.038	0.126	0.042
	t = 2.090**	t = 0.389	t = 1.346	t = 0.789
CMA	0.024	−0.041	0.044	−0.018
	t = 0.204	t = −0.522	t = 0.586	t = −0.428
Observations	60	60	60	60
R^2	0.092	0.158	0.143	0.084
Adjusted R^2	0.008	0.080	0.063	−0.0003
Residual Std. Error (df = 54)	0.011	0.007	0.007	0.004

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

Table C.17.2 – Fama French Five-Factor alpha for AS Quartiles from 2009

	AS QUARTILES FROM 2009			
	Highest	2nd	3rd	Lowest
Alpha	0.0002	−0.0005	−0.001	−0.0001
	t = 0.123	t = −0.396	t = −0.622	t = −0.217
Mkt-Rf	−0.001	0.008	0.011	0.001
	t = −0.037	t = 0.310	t = 0.466	t = 0.068
SMB	−0.031	0.006	0.060	0.036
	t = −0.423	t = 0.094	t = 0.957	t = 0.974
HML	0.123	0.069	0.089	0.070
	t = 1.270	t = 0.803	t = 1.091	t = 1.447
RMW	0.235	0.092	0.139	0.115
	t = 1.555	t = 0.683	t = 1.082	t = 1.509
CMA	0.107	0.104	0.072	−0.010
	t = 0.926	t = 1.006	t = 0.740	t = −0.167
Observations	59	59	59	59
R^2	0.077	0.059	0.065	0.052
Adjusted R^2	−0.010	−0.030	−0.023	−0.038
Residual Std. Error (df = 53)	0.009	0.008	0.007	0.004

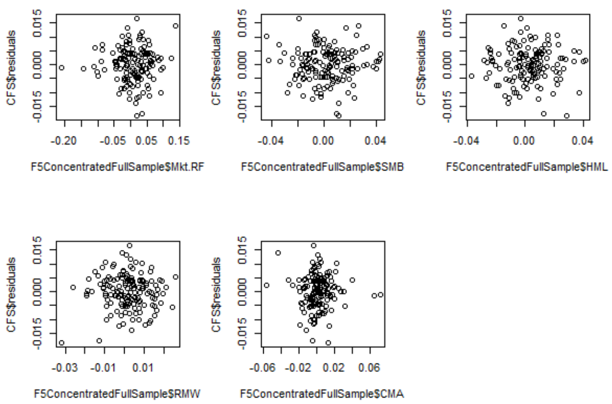
Note: *p<0.1; **p<0.05; ***p<0.01

APPENDIX D – MODEL DIAGNOSTICS

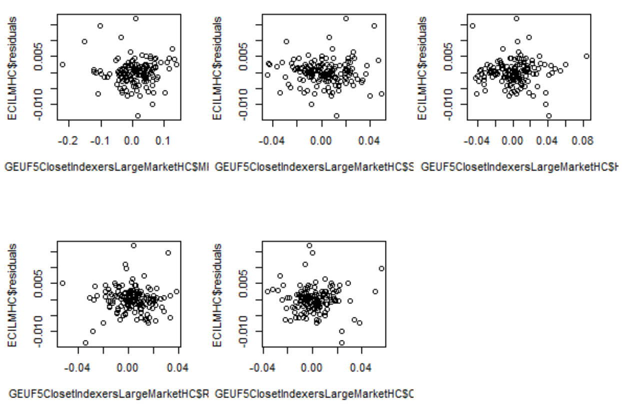
D.1 - MODELS FROM CREMERS & PETAJISTO (2009)

Testing for linearity and additivity

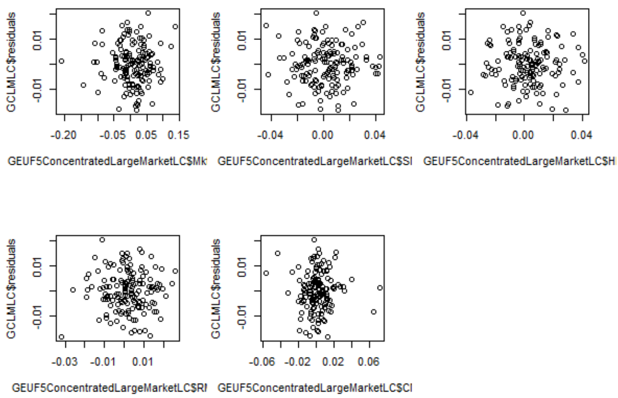
Model 1: *Full Sample Concentrated Fund*



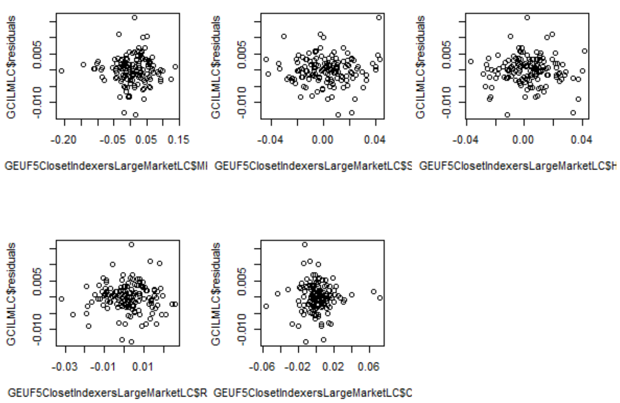
Model 2: *European Closet Indexers on Large Markets with High Correlation*



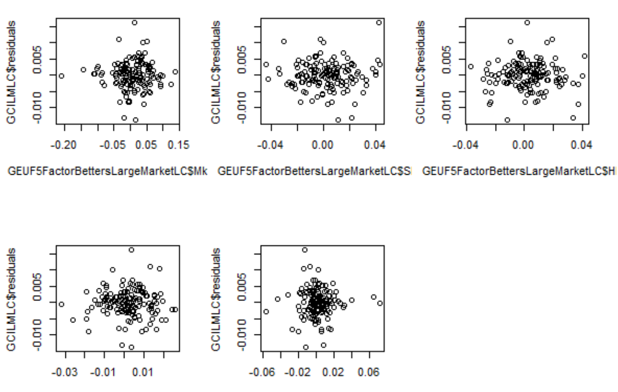
Model 3: *Global Concentrated on Large Markets with Low Correlation*



Model 4: *Global Closet Indexers on Large Markets with Low Correlation*



Model 5: *Global Factor Bettors on Large Market with Low Correlation*



Testing for Statistical Independence

Model 1: *Full Sample Concentrated Funds*

Durbin Watsons statistic:

```
lag Autocorrelation D-W Statistic p-value
  1      -0.0489511       2.07469   0.698
Alternative hypothesis: rho != 0
```

Model 2: *European Closet Indexers on Large Markets with High Correlation*

Durbin Watson statistic:

```
lag Autocorrelation D-W Statistic p-value
  1      -0.1788734      2.300974  0.0718
Alternative hypothesis: rho != 0
```

Model 3: *Global Concentrated on Large Markets with Low Correlation*

```
lag Autocorrelation D-W Statistic p-value
  1     -0.02344467      2.020451  0.9494
Alternative hypothesis: rho != 0
```

Model 4: *Global Closet Indexers on Large Markets with Low Correlation*

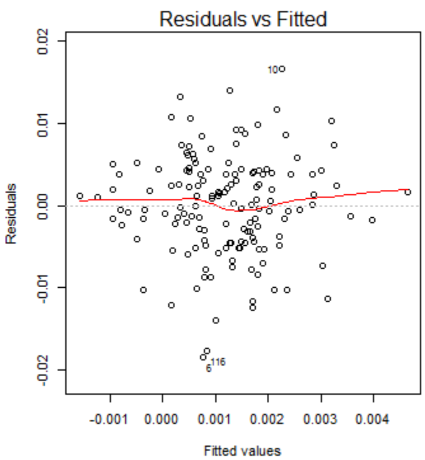
```
lag Autocorrelation D-W Statistic p-value
  1      -0.1625987      2.259508  0.1402
Alternative hypothesis: rho != 0
```

Model 5: *Global Factor Bettors on Large Market with Low Correlation*

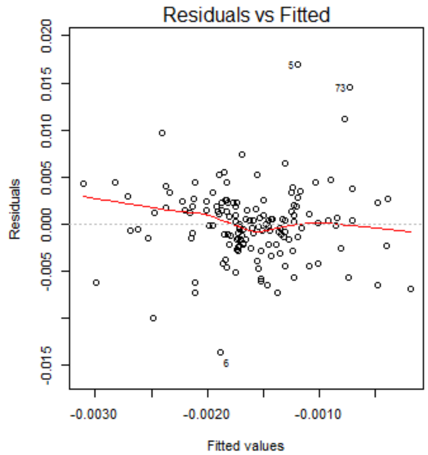
```
lag Autocorrelation D-W Statistic p-value
  1       -0.176044      2.346803  0.0386
Alternative hypothesis: rho != 0
```

Homoscedasticity

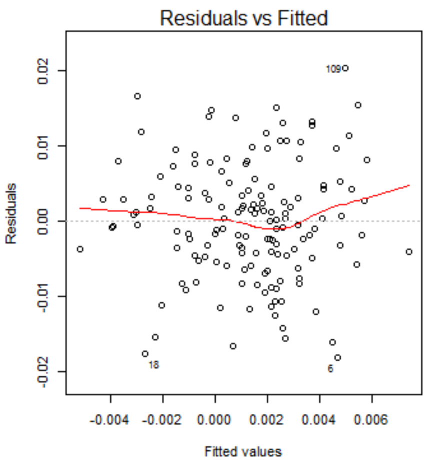
Model 1: *Full Sample Concentrated Funds*



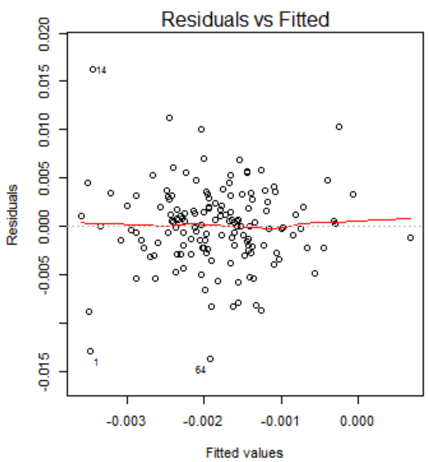
Model 2: *European Closet Indexers on Large Markets with High Correlation*



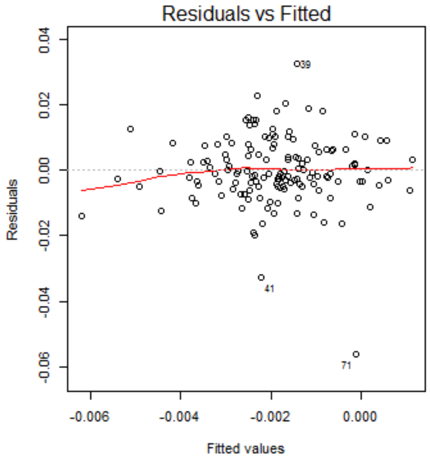
Model 3: *Global Concentrated on Large Markets with Low Correlation*



Model 4: *Global Closet Indexers on Large Markets with Low Correlation*

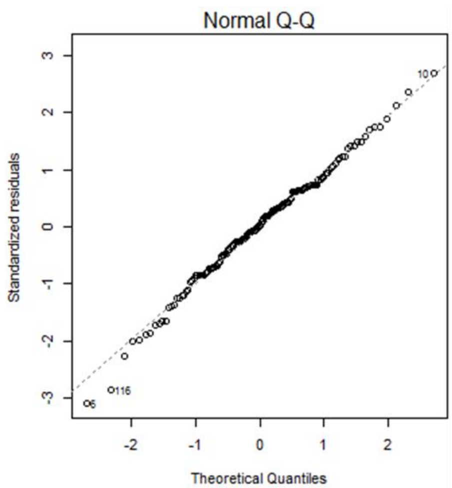


Model 5: *Global Factor Bettors on Large Market with Low Correlation*



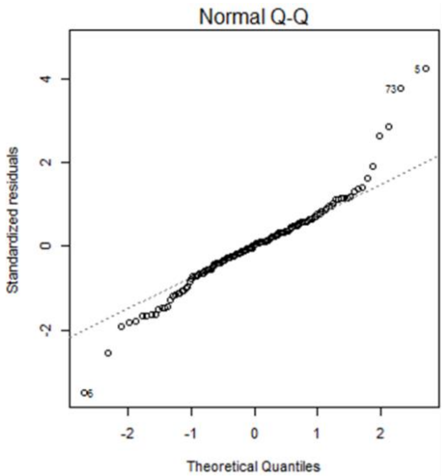
Normality

Model 1: *Full Sample Concentrated Funds*



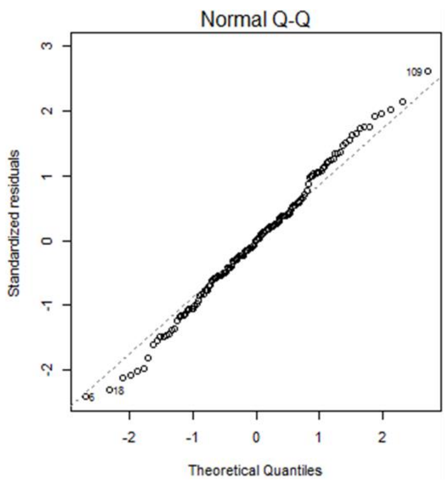

```
        Jarque-Bera test for normality

data:  CFS$residuals
JB = 2.2544, p-value = 0.2566

        Shapiro-Wilk normality test

data:  CFS$residuals
W = 0.99243, p-value = 0.6233
```

Model 2: *European Closet Indexers on Large Markets with High Correlation*



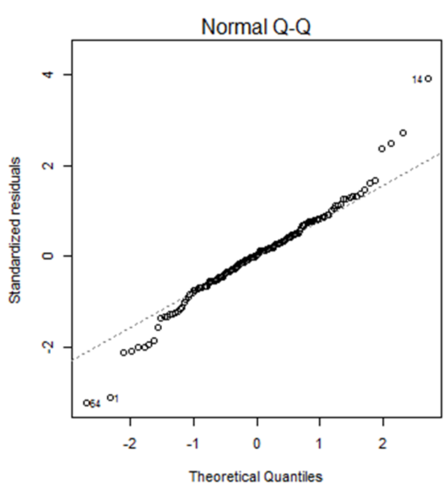

```
        Jarque-Bera test for normality

data:  ECILMHC$residuals
JB = 81.283, p-value < 2.2e-16

        Shapiro-Wilk normality test

data:  ECILMHC$residuals
W = 0.94203, p-value = 8.612e-06
```

Model 3: *Global Concentrated on Large Markets with Low Correlation*



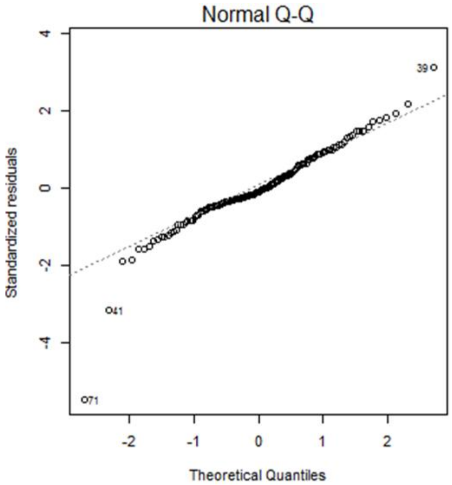

```
        Jarque-Bera test for normality

data:  GCLMLC$residuals
JB = 0.33133, p-value = 0.8319

        Shapiro-Wilk normality test

data:  GCLMLC$residuals
W = 0.99415, p-value = 0.8151
```

Model 4: *Global Closet Indexers on Large Markets with Low Correlation*




```
        Jarque-Bera test for normality

data:  GCILMLC$residuals
JB = 25.659, p-value = 0.0017

        Shapiro-Wilk normality test

data:  GCILMLC$residuals
W = 0.96927, p-value = 0.002117
```

Model 5: *Global Factor Bettors on Large Market with Low Correlation*

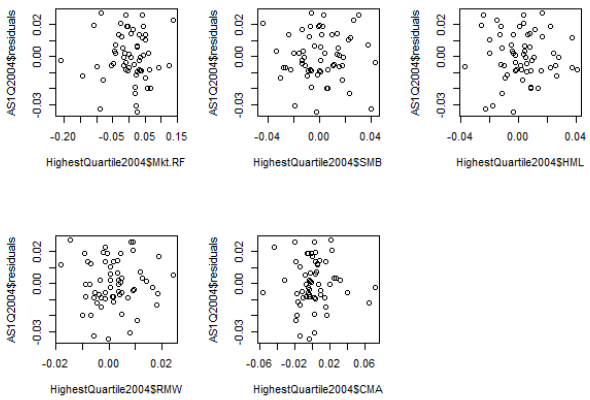



```
        Jarque-Bera test for normality

data:  GFBLMLC$residuals
JB = 221.73, p-value < 2.2e-16
        Shapiro-Wilk normality test

data:  GFBLMLC$residuals
W = 0.92798, p-value = 1.123e-06
```

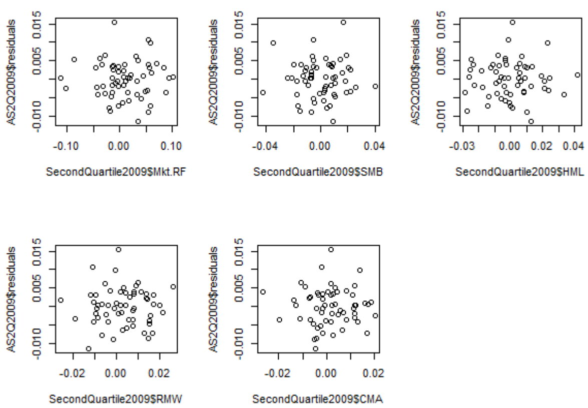
D.2 - MODELS ON AS QUARTILES

Testing for linearity and additivity

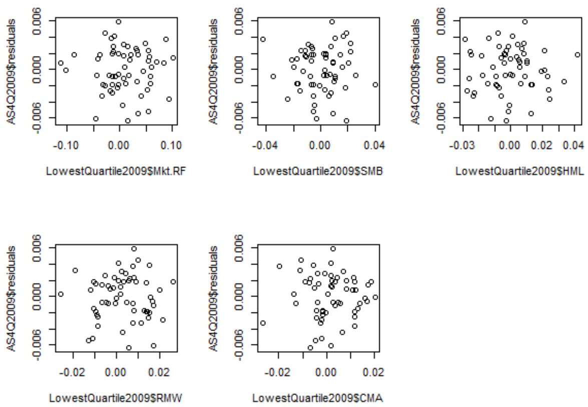
Model 1: *Highest AS Quartile from 2004*



Model 2: *2^{nd} AS Quartile from 2009*



Model 3: Lowest AS *Quartile from 2009*



Testing for Statistical Independence

Model 1: *Highest AS Quartile from 2004*

```
lag Autocorrelation D-W Statistic p-value
  1      0.05115179      1.896964   0.604
Alternative hypothesis: rho != 0
```

Model 2: *2nd AS Quartile from 2009*

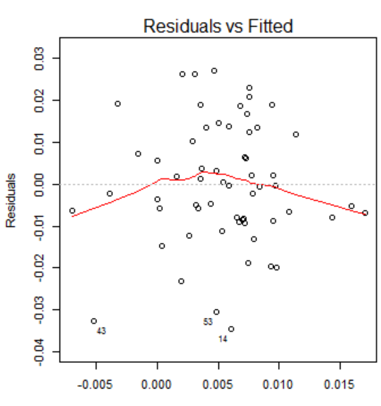
```
lag Autocorrelation D-W Statistic p-value
  1     0.008819625      1.982205  0.9456
Alternative hypothesis: rho != 0
```

Model 3: Lowest AS *Quartile from 2009*

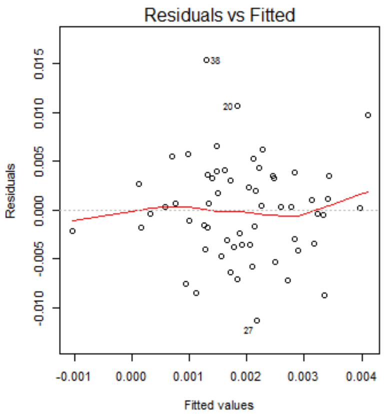
```
lag Autocorrelation D-W Statistic p-value
  1      -0.1286794      2.216215   0.405
Alternative hypothesis: rho != 0
```

Homoscedasticity

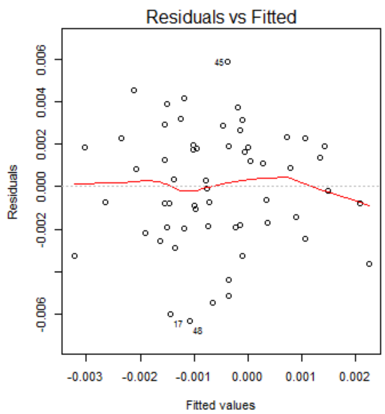
Model 1: *Highest AS Quartile from 2004*



Model 2: *2nd AS Quartile from 2009*

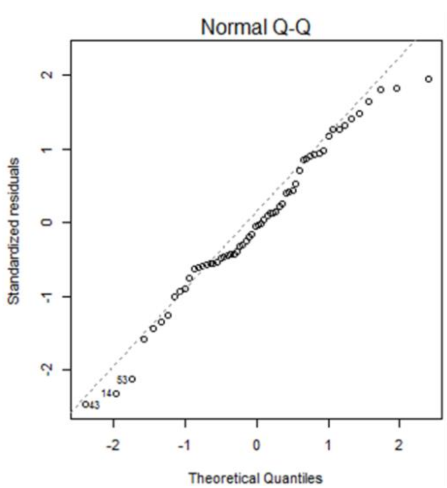


Model 3: Lowest AS *Quartile from 2009*



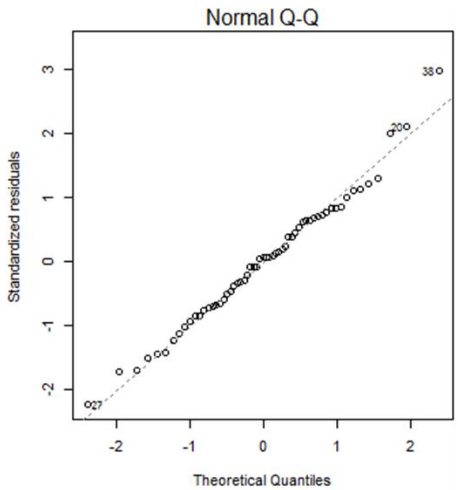
Normality

Model 1: *Highest AS Quartile from 2004*



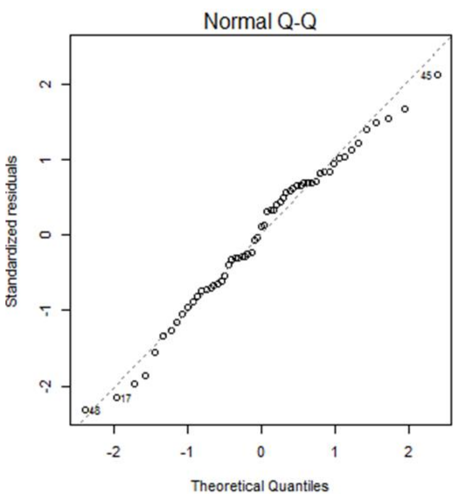

```
        Jarque-Bera test for normality

data:  AS1Q2004$residuals
JB = 0.45398, p-value = 0.7671

        Shapiro-Wilk normality test

data:  AS1Q2004$residuals
W = 0.97764, p-value = 0.3372
```

Model 2: *2nd AS Quartile from 2009*




```
        Jarque-Bera test for normality

data:  AS2Q2009$residuals
JB = 1.5938, p-value = 0.3245

        Shapiro-Wilk normality test

data:  AS2Q2009$residuals
W = 0.98598, p-value = 0.7306
```

Model 3: Lowest AS *Quartile from 2009*




```
        Jarque-Bera test for normality

data:  AS4Q2009$residuals
JB = 1.3471, p-value = 0.4006

        Shapiro-Wilk normality test

data:  AS4Q2009$residuals
W = 0.98099, p-value = 0.4832
```

APPENDIX E – MATHEMATICAL DEDUCTION

$$TE = Std.Dev(\sum_{t=1}^{T}\sum_{i=1}^{n}(\omega_{F,i} - \omega_{I,i}) * R_{i,t})$$

$$TE^2 = Var(\sum_{t=1}^{T}\sum_{i=1}^{n}(\omega_{F,i} - \omega_{I,i}) * R_{i,t})$$

$Set\ \Delta_i = \ \omega_{F,i} - \omega_{I,i}$

Hence,

$$TE^2 = Var(\sum_{t=1}^{T}\sum_{i=1}^{n}\Delta_i * R_{i,t})$$

$$Use : Var\left(\sum_{i=1}^{n} A_i\right) = \sum_{i=1}^{n} Var(A_i) + \sum_{i=1}^{n}\sum_{\substack{j=1 \\ j\neq i}}^{n} Cov(A_i, A_j)$$

Hence:

$$TE^2 = \sum_{t=1}^{T}\sum_{i=1}^{n}\Delta_i^2 * Var(R_{i,}t) + \sum_{t=1}^{T}\sum_{i=1}^{n}\sum_{\substack{j=1 \\ j\neq i}}^{n}\Delta_i\Delta_j * Cov(R_{i,t}, R_{j,t}) + terms\ involving\ Cov(R_{i,t}, R_{j,s}),$$

i.e. covariances between different times.

We assume that covariances:

$Cov(R_{i,t}, R_{i,s}) = 0$, s ≠ t, and that cross covariances $Cov(R_{i,t}, R_{j,s}) = 0$, j ≠ i, s ≠ t.

Setting: $Var(R_{i,}t) = \ \sigma_i^2$

$$Cov(R_{i,t}, R_{j,t}) = \ \rho_{ij}\sigma_i\sigma_j$$

I.e. all quantities are averaged wrt time t, we have:

$$TE^2 = \sum_{t=1}^{T}\sum_{i=1}^{n}\Delta_i^2 * \sigma_i^2 + \sum_{t=1}^{T}\sum_{i=1}^{n}\sum_{\substack{j=1 \\ j\neq i}}^{n}\Delta_i\Delta_j\rho_{ij}\sigma_i\sigma_j$$

$$T(\sum_{i=1}^{n}\Delta_i^2\sigma_i^2 + \sum_{i=1}^{n}\sum_{\substack{j=1 \\ j\neq i}}^{n}\Delta_i\Delta_j\rho_{ij}\sigma_i\sigma_j)$$

Further assuming that ρ_{ij} is average across all positions, we have

$$TE^2 = T(\sum_{i=1}^{n}\Delta_i^2\sigma_i^2 + \rho\sum_{i=1}^{n}\sum_{\substack{j=1 \\ j\neq i}}^{n}\Delta_i\Delta_j\sigma_i\sigma_j)$$

Where ρ is the average correlation.

$$TE = \sqrt{T} * (\sum_{i=1}^{n} \Delta_i^2 \sigma_i^2 + \rho \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \neq i}}^{n} \Delta_i \Delta_j \sigma_i \sigma_j)^{-\frac{1}{2}}$$

The sensitivity of TE wrt ρ is:

$$\frac{\delta TE}{\delta \rho} = \sqrt{T} * \frac{1}{2} (\sum_{i=1}^{n} \Delta_i^2 \sigma_i^2 + \rho \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \neq i}}^{n} \Delta_i \Delta_j \sigma_i \sigma_j)^{-\frac{1}{2}} * \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \neq i}}^{n} \Delta_i \Delta_j \sigma_i \sigma_j$$

$$\frac{\delta TE}{\delta \rho} = \frac{1}{2} * \frac{T}{TE} \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \neq i}}^{n} \Delta_i \Delta_j \sigma_i \sigma_j$$

APPENDIX F: VBA CODE USED IN THE ASSIGNMENT

SECTION 7...//RANDOMIZING THE SAMPLE OF EQUITIES.

```
Sub MSCIEMU()

Dim FillRange As Range, c As Range

Set FillRange = Range("F6:F55")

For Each c In FillRange

Do

c.Value = Int((240 - 1 + 1) * Rnd + 1)

Loop Until WorksheetFunction.CountIf(FillRange, c.Value) < 2

Next

End Sub
```

SECTION 7...//FINDING AVERAGE CORRELATION ON THE MARKET

```
Function AvgCorrelation(DataRange As Range)

'

Dim nRow As Long, nCol As Long

Dim i As Integer, j As Integer, j1 As Integer, j2 As Integer

Dim RtnData() As Double

Dim v1

Dim counts As Double, sum_correl As Double

Dim rtn1() As Double, rtn2() As Double

Dim MatColCount As Integer
```

```
'
AvgCorrelation = 0
MatColCount = 0
'
nRow = DataRange.Rows.Count
nCol = DataRange.Columns.Count
If nRow <= 2 Or nCol <= 1 Then Exit Function
'
ReDim RtnData(1 To nRow, 1 To nCol)
ReDim rtn1(1 To nRow)
ReDim rtn2(1 To nRow)
'
For i = 1 To nRow
   MatColCount = 0
   For j = 1 To nCol
      If DataRange(1, j).Value <> "" And DataRange(nRow, j) <> "" Then
         v1 = DataRange(i, j).Value
         MatColCount = MatColCount + 1
         RtnData(i, MatColCount) = v1
      End If
   Next j
Next i
'
counts = 0
sum_correl = 0
If MatColCount <= 1 Then Exit Function
'
For j1 = 1 To MatColCount
   For i = 1 To nRow
      rtn1(i) = RtnData(i, j1)
   Next i
```

```
'
    For j2 = j1 + 1 To MatColCount
        For i = 1 To nRow
            rtn2(i) = RtnData(i, j2)
        Next i
'
        counts = counts + 1
        sum_correl = sum_correl + WorksheetFunction.Correl(rtn1, rtn2)
'
    Next j2
'
Next j1
'
If counts > 0 Then AvgCorrelation = sum_correl / counts
'
End Function
```