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Active versus passive investing in emerging markets

An empirical study of the relationship between mutual fund performance and the degree of active fund management in emerging markets

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Master thesis in Financial Economics

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Abstract

The debate whether active funds add value compared to passive funds has mostly been limited to developed markets. In this study, we use a panel dataset to investigate whether emerging markets mutual funds' performance is positively related to their degree of active fund management. The scope is limited to all-equity mutual funds that invest broadly in emerging markets as opposed to mutual funds that invest in debt or have geographically concentrated portfolios. This is done to ensure adequate comparability between the mutual funds we examine. We find no significant performance differences between "closet indexers" (funds with active share below 60%) and truly active mutual funds. Further, regression results show limited to no relationship between the mutual funds' performance and their degree of activity. In sum, our findings suggest that the activity metrics Active Share and Tracking Error are not suitable to explain mutual fund performance in emerging markets. As a sub-analysis, we also investigate whether there are some mutual funds that consistently outperform the market. We find that across a 10-year period, only one out of 88 mutual funds in our sample managed to do so.

Preface

This thesis is written as a part of our master's degree with a specialization in Financial Economics at the Norwegian School of Economics (NHH).

Our interest for the subject was sparked by courses at NHH and at Columbia University, as well as our general interest for financial markets and our own investments in emerging markets. In addition, the topic of active funds marketing themselves as active, but being passive in practice, has recently been relevant in Norwegian media.

The process has been challenging and time-consuming, but also highly educational and interesting. We have gained a more in-depth knowledge of the theoretical basis we had at the outset, and our skills within treating large amounts of data have been vastly improved.

We would like to express our gratitude to our supervisor, Assistant Professor Darya Yuferova, who has provided valuable guidance and feedback on a topic we initially had limited knowledge of. Furthermore, we would like to thank Morningstar Direct and Martijn Cremers for answering our questions respectively regarding mutual fund data and Active Share.

Bergen, June, 2019

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1. Introduction

This paper examines the relationship between performance and degree of active management[1] for mutual funds that only invest in emerging markets[2]. We use a unique dataset that consists of performance and activity data for 88 emerging markets mutual funds in the time period 2009-2019.

The debate between active investing and passive investing have arguably been somewhat limited to developed markets, for instance reflected in how Carhart (1997), Sorensen et al. (1998), Malkiel (2003) and Cremers & Petajisto (2009) all examine mutual fund performance in the U.S. market. This paper contributes to this existing literature through its focus on emerging markets.

Cremers & Petajisto (2009) presented a new perspective on this debate with the introduction of Active Share. The metric measures how active mutual funds are in practice. Using this metric, the authors measured the relationship between fund performance and the degree of active fund management in the U.S. market. Interestingly, they found that the mutual funds with the highest Active Share outperformed their benchmarks, both before and after costs.

Active Share is an important basis for the analyses conducted in this thesis. To our knowledge, there are no other papers that examine the relationship between Active Share and mutual fund performance in emerging markets.

The metric has also been of relevance in Norway, as Døskeland (2016) used it in his argumentation in a lawsuit against DNB. The major bank was accused of marketing some of the company's funds as active, but metrics, including Active Share, indicated that the funds were managed passively. In May 2019, DNB lost the lawsuit and is required to pay 345 mNOK (around 40mUSD) to the 180,000 customers of the funds (Dagens Næringsliv, 2019).

Cremers & Petajisto's findings of a positive relationship between mutual fund performance and activity, in combination with how most existing literature within the field focus on developed markets, provide the main motivation behind this paper.

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[1] In this paper, active management is defined as a fund´s deviation from the benchmark´s portfolio holdings.

[2] Emerging markets are countries that have some characteristics of developed countries, but do not satisfy standards necessary to be termed developed markets. Such standards include, but are not limited to, domestic market size, market liquidity and openness to foreign investors (MSCI , 2014). See Appendix for MSCI's list of which countries comprise emerging markets.

By utilizing the most recent mutual fund data and by using the relatively new metric Active Share, we will in this thesis examine the following research question:

Is the performance of mutual funds that invest in emerging markets positively related to the mutual funds' degree of activity?

Here, we define performance as net and gross returns, Sharpe Ratio and, most importantly, Alpha. We measure the mutual funds' degree of activity through the metrics Active Share and Tracking Error. Our hypothesis is that the performance metrics are indeed positively related to Active Share and Tracking Error. To test this hypothesis, we perform two main analyses. In the testing of our hypothesis we utilize various forms of econometric techniques including, but not limited to, fixed effects models, pooled OLS regressions, and t-tests. In addition to our two main analyses, we perform a preliminary sub-analysis.

Of our three analyses, we start with conducting our sub-analysis. Here, we investigate whether or not some emerging markets mutual funds are consistently able to produce risk-adjusted superior returns compared to the market. The reason for starting with the sub-analysis is that it is highly relevant for investors that wish to invest in emerging markets, but are uncertain in the choice between mutual funds and more passive options, such as ETFs. Even if mutual fund performance indeed is positively related to activity, it would not be a relevant finding for retail investors if mutual funds continuously underperform the market. In such an instance, ETFs that replicate the market returns would be a better alternative. We find that a majority of mutual funds outperform the market in terms of pure returns, both before and after costs. However, there is no consistent outperformance when risk is accounted for. This suggests that the mutual funds take on higher risk than the market in their pursuit of beating their benchmark. Our findings are in line with what has become rather common knowledge in the world of finance – that outperforming the market consistently is extremely difficult, as reflected by the findings of Sorensen et al. (1998) and Malkiel (2003). For emerging markets specifically, our findings are similar to Chang et. al (1995), but conflicting in comparison to Dyck et al (2013).

In the first main analysis, we treat the degree of activity as a binary question and separate the mutual funds into two different groups based on their degree of activity. The first group consists of truly active mutual funds, whereas the second group consists of *potential closet indexers*. The latter group encompasses of mutual funds with an average Active Share of below 60%, as defined by Cremers & Petajisto (2009). Truly active mutual funds are defined as mutual funds with active share higher than 60%. We find that the vast majority of the mutual funds in our sample are truly active funds. Only 10 of the 88 mutual funds in our sample can be labeled as closet indexers, following Cremers & Petajisto's threshold of 60%. In each group, we calculate the average monthly returns, Sharpe Ratio and Alpha across the entire sample time period of 2009-2019 and test for statistical differences. The Alphas are calculated using three different factor models, which include CAPM, Carhart, and an extension of CAPM Redux model. We find that there are no statistical differences in performance between the two groups. This conclusion holds both gross and net of costs.

In the second main analysis, we examine whether there is a relationship between mutual fund performance and the degree of activity. Thus, in contrast to the second hypothesis, this analysis treats activity as a scale, rather than binary. We use the mutual fund's monthly returns, Sharpe Ratios and Alphas as dependent variables in different sorts of regression models, including pooled OLS, fixed effects and OLS. The independent variables are the mutual funds' monthly Active Share and Tracking Error, in addition to controls. We find that the Active Share and Tracking Error coefficients are not statistically significant. For the Active Share term, this is contradictory to what Cremers & Petajisto (2009) found for mutual funds in the U.S. market. To substantiate the findings, we perform rolling window regressions. This is done to examine the coefficients' beta across time and ensure that the conclusion is consistent independent of the time period in question.

Considering the results of the two main analyses, we reject our hypothesis and conclude that there is no significant relationship between emerging markets mutual fund performance and the degree of active fund management. This conclusion is however limited to all-equity mutual funds that invest in multiple emerging market countries. The reason for why the scope is limited in this way will be elaborated upon later.

The rest of this thesis will proceed as follows. Section 2 provides a review of related literature, including the debate between active and passive investing in general, factors that are unique for emerging markets, and lastly literature that cover active versus passive investing specifically in emerging markets. This is followed in Section 3 by an elaboration of our hypothesis and what we expect will be the outcome of our analysis, given prior research literature and our own intuition. In Section 4 we present the empirical methods we use to examine our hypothesis, in addition to elaborating upon the performance and activity metrics. Section 5 provides explanation of how we collected and cleaned the data. Our analyses and hypothesis testing constitute Section 6. Lastly, we summarize our findings in Section 7.

2. Literature review

This literature review is divided into three parts. The first part examines and presents past and current ideas of active investing in general compared to passive investing. The second part examines research related to the dynamics of emerging markets. Lastly, the third part combines the two prior parts and examines research covering active versus passive investing in emerging markets.

2.1 Active versus passive investing

Whether actively managed funds produce returns that outperform their benchmark index is widely discussed in literature. Sharpe (1991) argues that the very arithmetic of active management makes active investments a negative sum game which cannot beat passive investment by definition due to fees and transaction costs. He is supported by Fama & French (2010). However, Fama & French point out that even though the average mutual fund produce negative net alphas, there may be some mutual funds that produce positive alphas over longer time periods. Their research does nevertheless provide demoralizing results both for mutual fund managers and investors. From 10000 bootstrap simulations, they conclude that true alphas net of costs are negative for most mutual funds and that the few, if any, truly skilled managers are hidden by the mass of unskilled ones. Kosowski et al. (2007) does analysis with a similar bootstrap approach and argues that there in fact do exist superior managers with persistent skill.

The work on this thesis was largely influenced by the work of Cremers & Petajisto (2009). In analyzing domestic equity mutual funds in the US between 1980 and 2003, they presented a new measure of investment activity called active share. They provide, quite uniquely, evidence that the most active funds outperform their benchmarks both before and after expenses. The active share measure provides a new way to analyze activity as a scale, and such opportunity gives this thesis a broader perspective.

Petajisto (2013) did further research on the active share metric, and again found active funds to outperform their benchmarks, but also that closet indexers (funds marketed as active, but passive in practice) underperformed their benchmarks. Cremers & Pareek (2015) claim that both active share and trading frequency are important factors when assessing and predicting performance. They find that active mutual funds who trade infrequently outperform their benchmark by over 2% per year. Given these results, the superior funds seem to have an active portfolio with a low trading frequency, thus combining an active manager's set of skills in stock selection with a "passive" patience.

While Cremers & Petajisto (2009) claim that the most active funds indeed outperform their benchmarks, there are certainly contrasting papers on the other side of the spectrum. Malkiel (2003) provides evidence that strongly encourage passive investment strategies in all markets. Malkiel (2003) argues that near market efficiency in global equities means that transaction costs, or the cost of getting advantageous information, is too high to provide arbitrage opportunities. French (2008) also asserts that the costs of active investing are large and that it is increasingly important to think about passively managed investment strategies. Carhart (1997) finds negative correlations between performance and investment costs and demonstrate that close to all persistence in mutual fund performance can be applied to common stock return factors. The only persistence he finds hard to explain are concentrated around the underperformance by the funds with the lowest returns. In short, Carhart (1997) argues that skill does not necessarily lead to superior performance when compared to the market, but that the *lack* of skills can be a factor in underperforming funds. Sorenson et al. (1998) support the conclusion of mutual funds' general lack of benchmark outperformance with specific analysis. In 1997, for example, only 11% of mutual funds outperformed the S&P 500. These analyses, however, only pay attention to developed markets and does not specifically examine emerging markets as we do in this thesis.

How well fit one single statistical model can be on a large pool of funds is a question which can be raised for all papers, including the papers that indicate evidence of significant alphas, and those disembarking the existence of alpha. Funds differentiate a lot in strategies and holdings, thus one statistical model will probably be misspecified for at least some funds in a data set, according to Mamaysky et al. (2007). The authors propose backtesting a statistical model fund by fund, and only allow the model to predict a particular fund´s performance if the model proves past predictive success. In sum, one should be careful in drawing conclusion from a model that is used equally on all funds. Model misspecification is a concept that should be considered when arguing both for and against any findings.

2.2 Emerging markets

Early studies on emerging markets focused mainly on the diversification possibilities. Others have investigated the dynamics of emerging markets and how they might differ from developed markets.

Li et al (2003) suggests emerging markets provide opportunities for diversification, especially for investors that are exposed to short-selling constraints. Other literature, including Phylaktis & Ravazzolo (2005), supports the claim that emerging markets provide diversification opportunities. They do, however, find evidence that the integration of emerging markets into the world economy has reduced the overall diversification possibilities.

George Hoguet (2005) examines stock market performance and economic growth within emerging markets. He argues that increased growth rates in a market space will contribute to faster growth in earnings and profits for firms, thus prompting above average stock returns. Furthermore, he suggests other factors which can enable possibilities of superior performance in emerging markets compared to developed markets. Economies with a young population, with large needs for infrastructure and society developments as well as a large domestic demand, will over time perform better than developed economies. Although not directly related to this paper´s research question, Hoguet (2005) contributes to why emerging markets are interesting as an investment opportunity.

Bonser-Neal et al. (1999) used one emerging market, the Jakarta Stock Exchange (JSX) in Indonesia, to compare transaction costs with non-U.S. developed countries. They found that the prices of trading were modest compared to those reported for some European exchanges. The prices were affected by the same properties that previous studies have found in the U.S. markets, such as firm size, trade difficulty and who conducts the trade, with the latter being particularly significant. Furthermore, trades initiated by foreign traders had greater execution costs. Whilst the costs are moderate compared to some European exchanges, they are still a lot larger than those of the NYSE. Overall, this could imply larger transaction costs in some emerging markets, at least compared to the U.S.

Cajueiro & Tabak (2004) conduct an empirical study with the goal of ranking the efficiency of emerging markets. They find, interestingly, that emerging markets are less efficient when compared to Japanese and US equity markets.

According to the work of Stiglitz & Grossman (1980), the more inefficient markets are, the greater the difference in returns between those who expend resources to gain information and those who do not (the informed vs. the uniformed). Stiglitz & Grossman´s paper is known to introduce a paradox of the efficient market hypothesis[3]: since gaining information is costly, prices cannot perfectly reflect the information which is available, since if did, those who spend resources to gaining it would receive no compensation, leading to the conclusion that a perfectly efficient market is impossible.

Following the argumentation of Stiglitz & Grossman (1980) and the findings of Cajueiro & Tabak (2004), a hypothesis could be that capturing alpha may be easier in emerging markets as opposed to developed markets.

2.3 Active versus passive investing in emerging markets

Chang et al. (1995) reviewed potential investment opportunities to increase returns and diversification for U.S. retail investors via investing in closed-end funds. In addition to illustrating the benefits of international diversification, they further analyzed if the advantages reflected any superior performance of the funds. Jensen's alpha was calculated for all country specific closed-end funds. Of all the emerging markets closed-end funds researched, only the Mexico portfolio generated significant risk-adjusted returns in the period of 1987-1990. In sum, for an investor in the 90s there were close to no possibility of achieving superior performance when investing in country specific closed-end funds in emerging markets, according to Chang et al. (1995)

Further research to provide evidence on the prospect of capturing alpha in emerging markets includes Dyck et al. (2013). Their research evaluates institutional investors´ net returns relative to passive investing in markets which diverge in grades of efficiency. Their findings support benefits of active management in emerging markets. According to their results, active strategies outperforms passive ones in emerging markets by more than 180 basis point per year after costs, and that this conclusion remains significant when controlling for risk. They conclude that the general interpretation that active management does not pay should be reconsidered, at least in emerging markets.

[3] The efficient-market hypothesis (EMH) is a financial economics theory developed by Eugene Fama that states that asset prices reflect all available information. An implication of this theory is that it is impossible to outperform the market consistently on a risk-adjusted basis, since asset prices should only react to new information (Investopedia, 2019).

2.4 Literature review summary

The debate between active and passive investing has several nuances and different perspectives. A significant number of papers, for instance Malkiel (2003) and French (2008), assert that active investing does not outperform passive investing. Sorensen et al (1998) exemplifies this in how only 11% of mutual funds outperformed the S&P500 in 1997.

Cremers & Petajisto (2009) introduce a new metric for measuring the degree of active fund management called active share, and provide evidence that the most active funds outperform passive funds, both before and after costs.

Cajueiro & Tabak (2004) provide evidence that some emerging markets are less efficient than developed markets. Stiglitz & Grossman (1980) suggest that inefficient markets provide opportunity to produce excess returns for those who expend resources to acquire information. Thus, through combining the findings of Stiglitz & Grossman (1980) and Cajueiro & Tabak (2004), one could suggest that active investment could be preferable in emerging markets.

Chang et al. (1995) argue that in the 90s there were very limited possibilities of achieving abnormal performance when investing in emerging markets, whereas Dyck et al. (2013) argue that active strategies outperform passive strategies after costs by 180 basis points per year. The diverting perspectives in these papers show how there is no clear consensus on whether active investing is superior to passive investing in emerging markets.

3. Hypothesis

In the following, we recapitulate and elaborate upon the reasoning behind our main hypothesis and our sub-hypothesis. The hypotheses are mostly based on prior empirical research, but also on our own assessment.

Hypothesis 1 (main hypothesis): Emerging markets mutual fund performance is positively related to the degree of active fund management

Hypothesis 2 (sub-hypothesis): There are some emerging markets mutual funds that are able to consistently outperform the market

We expect that more active mutual funds outperform less active mutual funds. This is mainly based upon the findings of Cremers & Petajisto (2009), who found that funds with higher active share outperformed those funds with low active share in the U.S. market. We see no apparent reason for why one would expect other results in emerging markets as opposed to the U.S. market.

Our expectations for the results of the examination of our sub-hypothesis are more unclear. On the one hand, most of past research suggests that mutual funds outperforming the market consistently is, in general, extremely rare. On the other hand, astute mutual funds may be able to utilize the alleged market efficiencies (Cajueiro & Tabak, 2004) in emerging markets.

4. Methodology

This chapter presents the metrics and empirical methods we use to examine our hypotheses. Firstly, we describe how we measure the degree of active management for a fund. Secondly, we describe how we evaluate fund performance. Lastly, we elaborate upon the empirical methods used to study the relationship between performance and active management.

Regressions constitute an important part of this study´s analyses. Some regressions are simple, with few independent variables. Others include pooled panel regression and fixed effects models consisting of input from factor models. In addition to regressions, t-tests, Mann-Whitney U-tests and descriptive statistics will also be employed to form the basis for the analyses of our hypotheses.

4.1 Metrics for calculating degree of active fund management

Active share, tracking error and turnover are common metrics used to examine the degree of active management (Cremers & Petajisto, 2009). We will focus on active share and tracking error in our analyses. Both metrics have their strengths and weaknesses and using both rather than just one will allow for a more comprehensive picture of the relationship between mutual fund performance and the degree of active management. We will now elaborate upon active share and tracking error, in addition to explaining why we do not use turnover.

Active Share

Active share is the newest of the mentioned metrics to be popularized. It can simply be interpreted as the “fraction of the portfolio that is different from the benchmark index”, as described in Cremers & Petajisto (2009).

Cremers & Petajisto (2009) defines active share as the following:

$$\boldsymbol{Active\ share} = \frac{\mathbf{1}}{\mathbf{2}}\sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{N}}\left\lceil \boldsymbol{W}_{\boldsymbol{fund},\ \boldsymbol{i}} - \boldsymbol{W}_{\boldsymbol{index},\ \boldsymbol{i}} \right\rceil, \boldsymbol{i} \qquad (1)$$

where $W_{fund,\ i}$ is the fund's portfolio weight in holding i and $W_{index,\ i}$ is the weighting of holding i in the benchmark portfolio, making $W_{fund,\ i} - W_{index,\ i}$ the deviation between the fund and the benchmark for holding *i.* Each deviation from a benchmark needs to be divided by two, since each deviation in a fund relative to the benchmark results in both an overweight in whatever position the fund deviates towards and an underweight in the benchmark position.

If, for instance, three stocks constitute one third each of a benchmark portfolio, and a fund is equally invested in two of these stocks but not at all in the third, the active share of the fund would be 33.33%. For a fund to be assessed as different from its benchmark portfolio, it must have an active share that is different from zero. A fund that does not hold short positions or uses gearing will always have an active share between zero and 100.

Cremers & Petajisto (2009) suggest that funds with active share below 60% are "potential closet indexers", funds that rather closely track a benchmark while having costs that are similar to those of truly active funds. The 60% threshold is however to be considered as a guideline, rather than a strict pass/fail test. Cremers & Petajisto argue that, given the historically positive skew of the distribution of stock returns, at most half of the benchmark assets will outperform the benchmark return. Thus, this suggest that a reasonable minimum active share that is consistent with active management is 50%, since this would be the active share of a fund that simply took a position in only the half of the index that was expected to outperform. The authors suggest that 50% is the bare minimum, and that the extra 10% is more subjective. The authors write that, ultimately, the 60% threshold is a consequence of the finding that funds under this limit underperform. The threshold may also be influenced by the fact that Cremers & Petajisto (2009) in their paper cover the U.S. market. In for example Norway, with fewer investing options, the threshold may be considered too strict, whereas in a multinational market such as emerging markets, the threshold may not be strict enough. We will elaborate on this point in the analysis.

Tracking error

Tracking error is the traditional metric used to measure active management (Cremers & Petajisto, 2009) Tracking error measures the volatility of the difference in returns of a fund compared to its benchmark.

$$\textbf{\textit{Tracking Error}} = \sqrt{\frac{\sum_{i=1}^{n}(R_P - R_B)^2}{N-1}}, \tag{2}$$

where R_P is the return of the fund in question, R_B is the benchmark return, and N is the number of periods. A weakness with tracking error, as described by Cremers & Petajisto (2009), is that different investment strategies can impact the tracking error level when the same benchmark is used for multiple mutual funds, which it often is. For instance, a fund that picks stocks across a vast range of sectors may have a lower tracking error than a fund that is sector-specific because of the prior's higher diversification. However, the diversified fund may be more active in their stock picking than the sector-specific fund. This weakness is a further argument for why we include active share, and not just tracking error, as a measure of how active the funds are.

Comparing active share and tracking error

Active share is unique in the sense that it directly compares the holdings of a fund with the holdings of the benchmark, unlike the traditional metric tracking error that is based on differences in returns and standard deviation between a fund and its benchmark index. Another potential advantage of active share is that it is calculated as a snapshot at a given point in time, unlike the tracking error that is based on historical returns (Khusainova & Mier, 2017).

While we view these as positive arguments for using active share, the metric is not without its weaknesses. Choosing what constitutes the benchmark index is obviously an important element. Changing the benchmark index may severely impact a fund's active share. How this potential problem is dealt with in this paper is elaborated upon in the next chapter.

A further complicating element can be if a fund tracks several indexes at the same time. Khusainova & Mier (2017) notes how "… active share has been well-received outside academia as a possible indicator of potential future outperformance". With this in mind, funds may seek ways to "manipulate" their active share, although this is a speculative claim. While the mentioned complications may be problematic in the calculation of active share, it should be noted that tracking error is also subject to the same complications since the calculation of tracking error also requires one to choose a benchmark portfolio.

While both tracking error and active share measure degree of activity, they measure different aspects of the degree of activity, according to Cremers & Petajisto (2009). Tracking error emphasizes systematic factors, while active share weighs all active bets equally, not dependent on whether the risk is diversified away or not. They write that tracking error serves as a proxy for factor bets while active share is a proxy for individual stock picking. Factor bets, or "factor timing", involves investing in factor portfolios such as a specific industry that the fund manager believes will perform well. Individual stock picking involves investing in individual stocks that the fund manager believe will outperform a given benchmark. Figure 1 below depicts different investment strategies and their relation to active share and tracking error.

Investment strategies´ relation to Active Share and Tracking Error

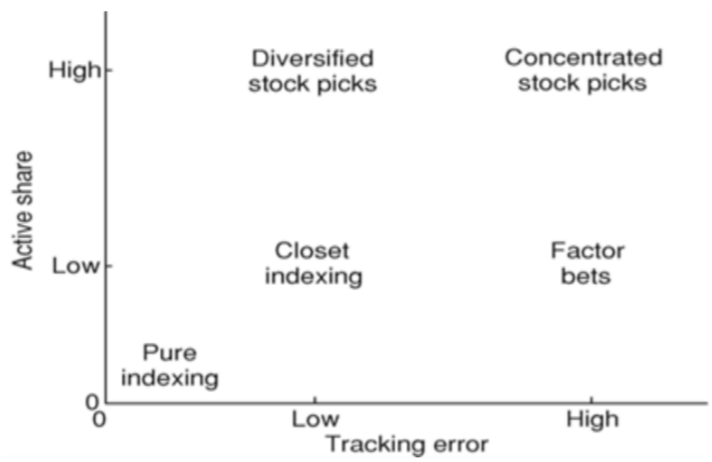

Figure 1: *Investment strategies' relation to Active Share and Tracking Error. Source: Cremers & Petajisto (2009)*

The different aspects and nuances of active management highlight how multiple metrics should be used in calculating the degree of active management, as doing so will allow for a more comprehensive picture and potentially reveal nuances.

Turnover

Turnover is another metric that is often used to describe the degree of activity for a fund. How active a fund is can, in simple terms, be considered along two dimensions. The first dimension includes to what degree a fund deviates from a benchmark in its portfolio holdings. The second dimension of activity relates to how often a fund buys and sells shares, as discussed in Cremers

& Petajisto (2009). In this thesis, the emphasis is on the first dimension of activity. This is the reason for why we do not include turnover in our analysis.

4.2 Metrics for evaluating performance

In evaluating the performance of the funds, we use three different types of metrics. Firstly, simple monthly returns, both before and after costs. Secondly, risk-adjusted returns through Sharpe ratios, and finally, alpha. In the following, we elaborate upon how we chose what we perceive as the most relevant benchmark, in addition to explaining Sharpe ratio. The calculation of each fund's alpha is covered in section 4.3.

Choosing a relevant benchmark

There are three dominating ETFs for emerging markets, commanding over 80% of total assets allocated to emerging markets ETFs according to the Lazard Report (Khusainova & Mier, 2017) and ETFdb.com. These are Vanguard FTSE Emerging Markets ETF (ticker: VWO), iShares MSCI Emerging Markets Index ETF (EEM) and iShares Core Emerging Markets ETF (IEMG). The *market* in this paper is proxied by using the average return of these three ETFs. It can be noted that the returns of these ETFs are almost identical. The reason behind using the ETFs return rather than for example index returns is that the ETFs represent the closest one can get to investing in "the market". In terms of gross returns, the distinction is rather trivial: a simple regression with the MSCI Emerging Markets Index as the dependent variable and the ETF average return has a statistically significant coefficient of 0.995 and an R^2 of 99%. Investing in the market does however entail some costs, and using the ETFs allows for a net of cost comparison between investing in a mutual funds versus the market. The cost of investing in the market is calculated as the average net expense ratio of the three major ETFs.

Sharpe ratio

In 1966, William Sharpe introduced the performance metric "reward-to-variability-ratio", now commonly known as the Sharpe ratio. The ratio shows a portfolio's average excess return over the risk-free rate, adjusted for the average standard deviation which functions as a proxy for the amount of risk. Investors wish to maximize the Sharpe ratio and thus achieve a high amount of return given a certain risk-level.

$$\boldsymbol{S_p} = \frac{\boldsymbol{r_p - r_f}}{\boldsymbol{\sigma_p}}, \tag{3}$$

where S_p is the Sharpe ratio, r_p is the portfolio's return, r_f is the risk-free rate and σ_p is total risk, measured as the standard deviation of the portfolio's return (Sharpe, 1966).

4.3 Regression and factor models

The main purpose of the regression models in this paper is to examine the relationship between the degree of active management and fund performance. Another benefit is that based on the factor regression models we can possibly infer something about the strategies of the mutual funds in our sample.

In the following, we introduce the factor models that comprise the first regression models. These factor models include the CAPM, Carhart's four-factor model and an extended International CAPM Redux. CAPM and Carhart's four-factor model are commonly used to assess mutual fund performance, while the International CAPM Redux is a more recent model that has yielded impressive results. Availability of data is a limiting factor, resulting in that we will use proxies for some of the factors, rather than the explicit methodology used in the papers we quote. How these factors for each model are calculated, with inspiration from Fasano & Gallappo (2016), is explained below.

Finally, the regressions that examines the relationship between the degree of active management and fund performance are elaborated upon.

CAPM

The Capital Asset Prizing Model (CAPM) was introduced by Sharpe, Linter and Mossin during the 1960s and gives a theoretical explanation for the relationship between risk and returns. Especially relevant for our study is also how CAPM reveals a fund's excess return over the market. The alpha can be interpreted as out- or under-performance compared to a benchmark (Sharpe, 1964). The CAPM expressed formally is as follows:

$$\boldsymbol{R_{it} - R_t^F = \alpha_i + \beta_i^M[R_t^M - R_t^F] + \varepsilon_{it},} \tag{4}$$

where R_{it} = return of fund *i* at time *t*, R_t^F = risk-free rate at time *t*, α_i = risk adjusted excess return of fund *i*, β_i^M = fund *i*'s exposure to systematic market risk, R_t^M = market return in USD at time *t*, and ε_{it} = error term of fund *i* at time *t* (unsystematic risk).

In this paper, R_t^M is defined as the return of MSCI Emerging Markets Index, and R_t^F is the yield of the one-month U.S. treasury bill.

Carhart four-factor model

The Carhart four-factor model is an extension of the CAPM and the Fama-French three-factor model. Compared to CAPM, three more factors are added to equation. These are the size factor "Small minus big" (SMB), the value factor "High minus low" (HML), and the momentum factor (UMD). Formally:

$$\boldsymbol{R_{it} - R_t^F = \alpha_i + \beta_i^M[R_t^M - R_t^F] + \beta_i^{SMB}SMB_t + \beta_i^{HML}HML_t + \beta_i^{UMD}UMD_t + \varepsilon_{it}}, \quad (5)$$

where SMB_t = size factor at time *t*, HML_t= value factor at time *t*, UMD_t = momentum factor at time *t*, β_i^{θ} = fund *i*'s factor exposure to θ, and θ = respective risk factors in the model.

SMB is in this paper calculated by subtracting the returns of the MSCI EM Large Capitalization Index from the MSCI EM Small Capitalization Index, HML through subtracting the MSCI EM Growth Index from the MSCI EM Market Value Index, and lastly the UMD factor is proxied through the returns of the Invesco DWA Emerging Markets Momentum ETF (Invesco Distributors , Inc., 2019). We use Invesco´s ETF for two reasons. Firstly, because MSCI's Emerging Markets Momentum Index was significantly correlated with the standard MSCI Emerging Markets Index, such that using MSCI's momentum index would result in multicollinearity problems. Secondly, because Invesco's ETF was the only emerging markets momentum ETF that covered the entire time-period of our dataset.

International CAPM Redux - extended

The last factor model we use is an extended version of the International CAPM Redux. We view this model as especially relevant for our paper as the International CAPM Redux includes currency factors. The mutual funds that we examine invest in a multitude of different countries and are thus subject to currency risk. A fund can hypothetically not produce returns in local currencies, but nonetheless appear to be profitable due to currency appreciation or depreciation. In addition to the CAPM factor (here in local currency), the International CAPM Redux model adds two currency factors: the "carry" factor and the "dollar" factor. The carry factor is the average excess return earned by an investor that goes short (long) in a portfolio of low (high) interest rate currencies (Brusa, Ramadorai, & Verdelhan, 2014). The dollar factor is the average excess return of an investor that borrows in U.S. dollars and invests in a broad portfolio of foreign currencies. Brusa et al. (2014) describe that a substantial fraction of the variation in bilateral exchange rates can be captured by these two factors. Again, due to limited data availability, this paper uses simplified proxies for these factors. We also modify the carry factor to only include emerging markets and add the factors included in Carhart's four-factor model for any additional fitting accuracy.

The final modified CAPM Redux model is formally formulated as the following:

$$\boldsymbol{R_{it} - R_t^F = \alpha_i + \beta_i^M\left[R_t^M - R_t^F\right] + \beta_i^{SMB}SMB_t + \beta_i^{HML}HML_t + \beta_i^{UMD}UMD_t + \beta_i^{Carry}Carry_t + \beta_i^{Dollar}Dollar_t + \varepsilon_{it}} \quad (6)$$

The carry factor proxied through the monthly returns of Bloomberg's Cumulative FX Carry Trade Index for 8 Emerging Markets, whereas the Dollar factor is proxied through the Federal Reserve's U.S. Dollar Index, which tracks the strength of the dollar against a basket of major currencies.

Examining the relationship between performance and degree of active fund management

All the factor models include an alpha-term (α_i). As mentioned, alpha can be interpreted as out- or under-performance compared to a benchmark (Sharpe, 1964). We test whether there is a relationship between alpha and the degree of active management through regression analysis. We calculate the alpha for each fund from the factor models regressions. Subsequently, we use these alphas as the dependent variable in a regression. The independent variables in this regression is each fund's average active share and tracking error. Formally:

$$\boldsymbol{\alpha = c + AS + TE + \varepsilon,} \quad (7)$$

where AS = active share, TE = tracking error, c = the intercept when both active share and tracking error equals zero, and ε = variation in alpha that cannot be explained by active share and tracking error. If the regression results show that the AS-term or TE-term is positive and statistically significant, one would conclude that there is a positive relationship between the degree of active fund management and outperformance of the benchmark.

The regression as formulated in regression (7) examines whether there is a linear relationship between alpha the activity metrics. A relationship between the variables, if existent, is not however necessarily linear. It may be that some degree of activity is optimal, but that having a very high level of activity has drawbacks. For this reason, we also include squared terms of active share and tracking error as independent variables.

We also conduct the regressions with *net* alphas (and net returns) as dependent variables. Since more active funds arguably need more resources than passive funds in order to conduct thorough analysis, active funds may have higher costs. If active funds are unable to achieve a better gross performance than passive funds, the relationship between performance and activity may be negative due to the potentially higher costs that being an active fund entail.

We conduct similar regressions as in equation (7) for examining returns and Sharpe ratios. The independent variables are in this instance funds´ monthly active share and tracking error (and their squared terms), whereas monthly returns and Sharpe ratios serve as dependent variables.

Fixed effects

Year dummies are included in the regression that is based on equation (7). This is akin to regressions in Cremers & Petajisto (2009) and is done to account for potential unobserved year-specific factors and thus capture any fixed effects within the year. Hypothetically, the relationship between mutual fund performance and activity could be impacted by how well the market is doing. For instance, more active funds could be more exposed in bull-markets due to their lower amount of diversification compared to more passive funds (or, active funds could be less exposed through taking measures to limit their downside in bull-markets).

Fund fixed effects are included to account for fund specific endogenous variables. Hypothetically, fund size may be an example of such an endogenous variable. Sufficiently large mutual funds may struggle to find enough attractive investment opportunities to allocate their large capital base optimally, resulting in lower returns than smaller and more agile mutual funds. Further, in an effort to keep their large customer base, the mutual fund may to a larger extent replicate the index to avoid underperforming its benchmark by a significant amount, with such a strategy resulting in a lower active share.

Rolling window regressions

Our dataset contains data for the time-period 2009-2019. We cannot rule out that some of the coefficients we calculate in regressions are time-varying, for instance caused by mutual funds changing their strategy over time, or that the relationship between mutual fund performance and degree of mutual fund activity is impacted by time-varying market conditions. For this reason, we perform rolling window regressions for the regression in Section 6.3. We only do this for this section since it contains the most vital regression in answering our research question. We use windows of one year and calculate the coefficients' 95% confidence intervals. All results from the rolling window regressions are included and elaborated upon in the Appendix.

4.4 Validity of the models

A set of assumptions need to be satisfied for OLS models to be BLUE (best linear unbiased estimator) such that inference of the model is valid and robust (Woolridge, 2015). For valid inference to be possible, measures are made in this paper for regression models that do not satisfy the BLUE requirements.

In the following, we describe the required assumptions in addition to how we deal with instances where the requirements are not met.

Strict exogeneity

The conditional expected value of the residual must be zero, meaning that the error term is unrelated to any given explanatory variable x at any given time, $E(\varepsilon_t|x_t) = 0.$ If this assumption is not upheld, we have endogeneity. In such an instance the estimates would not be consistent nor unbiased (Woolridge, 2015). We acknowledge that endogeneity issues may impact our analysis. Such issues can be caused both by unobservable (or observable, but not included in our models) fund characteristics and possible reverse-causality/simultaneity.

A potential source of endogeneity in our dataset could be that individual heteroscedasticity among the mutual funds disturb the relationship between performance and degree of activity. A way of solving this problem is to use a fixed effects model, for instance like applied in Himmelberg et al. (1999), where within-group transformation eliminates time-invariant company-specific characteristics.

Homoscedasticity

Constant variance for the error term for all values of x, $var(\varepsilon_t|x_t) = \sigma^2$, is called homoscedasticity, whereas the opposite case is called heteroscedasticity. Inference is not valid without homoscedasticity, as the model would not be efficient. Testing for heteroscedasticity can be done in multiple ways, for instance by using a Breusch-Pagan test. To solve heteroscedasticity issues one must use robust standard errors (Woolridge, 2015), as we have done in this paper.

Serial correlation

With absence of serial correlation, there is no dependence between residuals across time. Akin to a model having heteroscedasticity, the model will not be efficient if serial correlation is present. Presence of serial correlation can be tested by using a Durbin-Watson test (Woolridge, 2015). Problems with presence of serial correlation in the dataset can be corrected by using relatively simple adjustments to the regression in question. With signs of autocorrelation, we use Cochrane-Orcutt estimation to circumvent the problem. We will elaborate upon this in the Appendix.

Normally distributed residuals

The residuals have to be normally distributed in order for the BLUE requirements to be upheld. The central limit theorem does however say that inference is valid if the number of observations is sufficiently large (LaMorte, 2016). The lower limit that can be accepted as sufficient for normal data series is 30 observations. In this paper, we ensure no regressions or t-tests are made with an amount of observations that is less than the lower limit.

No multicollinearity

Multicollinearity occurs in multivariate regressions where two or more independent variables are highly correlated with each other. A consequence of multicollinearity can be that an independent variable's coefficient does not appear statistically different from zero, despite being so in reality. This is because the regression in question is not able to isolate the highly correlated independent variable from each other.

If the correlation of a model's independent variables is high, the problem can be resolved by omitting variables (Woolridge, 2015). We utilize VIF-tests (Variance Inflation Factor) to test for correlation between the models' independent variables. Allison (2012) argues that VIF-values over 2.5 indicate possible multicollinearity. Multicollinearity was indeed a problem for our models at the outset, resulting in simplification being necessary. The models described in the last chapter originally included the return of some major emerging market countries´ stock indexes to capture if a fund had a concentrated country weighting, but these indexes were omitted due to VIF-values significantly higher than the 2.5 threshold. As mentioned, multicollinearity also proved to be a problem if we included the MSCI Emerging Markets Momentum Index, resulting in us using the Invesco's Momentum ETF as a proxy instead.

Stationarity

Stationarity refers to situations where the joint probability distributions remain constant; that is, the mean and variance of a variable remain constant over time. Presence of non-stationarity can lead to a spurious regression. In our dataset, such a scenario could for instance be the case if the degree of activity changes over time. Mutual funds could, hypothetically, over time lift their degree of activity to distinguish themselves from accusations of being potential closet indexers. However, stationarity is viewed as a limited problem in panels with large N (number of panel members) and T (time-periods) (Pesaran, 2014). With our N=88 mutual funds and T=120 months, we disregard stationarity issues in our dataset.

5. Data

In this section, we present the data used to examine our research question. We start by describing the collection and cleaning of the mutual fund, ETF and factor data. Thereafter, we discuss potential biases in our data. An extensive work effort was required to collect and clean the data. With Morningstar Direct and Bloomberg as the sources, we consider the data to be reliable.

5.1 Mutual fund data

The mutual fund list consists of 88 funds, with data ranging from 2009 to 2019. The year 2009 was selected because there is limited data prior to this date. In our database, 19 of the 88 mutual funds were established as of 2009. We view the number of observations in 2009 as sufficient, but approaching its acceptable limit; thus, we limit the period to 2009-2019.

The list of funds was completed through various filters in Morningstar's mutual fund database. The aim was to have a list of funds that are comparable with emerging markets ETFs and for the funds to be accessible to retail investors. For this purpose, we required all funds to be invested in a broad range of emerging markets countries, and emerging markets only. This meant that portfolio weights were set to be higher than zero for several emerging markets countries, such as Brazil, Russia, India and China. Furthermore, a requirement was no investments in developed countries, nor frontier markets, again with the aim of being comparable to the benchmark indexes. A max-front load was set to 5000 USD for the purpose of making sure that the funds included in the sample are realistic investment alternatives for retail investors. The fund size was set to minimum 1m USD to avoid presence of incubation bias (Evans, 2008). We only include mutual funds that are categorized as “active”. Lastly, only all-equity funds were included, again to ensure adequate comparability.

Active share, tracking error, net expense ratios and Sharpe ratio data were collected through the Morningstar Portfolio Analysis Tool, whereas the funds’ returns were collected from Bloomberg. Not all funds included in the data sample had available net expense ratios. In these instances, the average net expense ratio of the available data is used. We collect the active share at the beginning of each month, whereas tracking error is the average of each month. Not all funds had available active share data and were thus removed from the fund list. This was however only the case for five mutual funds, so we do not consider it as an important source of potential bias. Both active share and the returns are monthly data. We consider the amount of observations we get from selecting monthly data as adequate, with over 6000 observations of returns. The ETF returns were also collected from Bloomberg. To ensure comparability, all return data were collected in USD.

As previously mentioned, the chosen benchmark index can have an important impact in the calculation of active share. There is, however, a “best fit index” option when choosing the benchmark index in Morningstar’s Portfolio Analysis Tool, ensuring that the active share is calculated with the most appropriate benchmark. For most funds, the best fit index was the MSCI Standard EM Index. Other benchmarks were MSCI Growth Index and Morningstar’s own EM Index, and a vast minority were other more specialized indexes, such as the MSCI Golden Dragon Index, which tracks the Chinese stock market. This implies that while we did filter in such a way that all funds are required to have some weight in several emerging market countries, some funds concentrate their portfolio to certain countries.

Lastly, we observed how several of the funds had similar names and were operated by the same company. Several of these funds had the same investment portfolios and were only differentiated by their share classes (e.g. “A”, “B”, “C). These share classes may have different fees and expenses, or be marketed towards specific investors (FINRA, 2008). We manually checked the returns of the funds that are under the same company umbrella. In instances where two or more funds had the same exact historical returns, we only kept the fund with the highest Total Net Assets, in accordance with prior literature that have encountered this issue (Gaspar, Massa, & Matos, 2006).

After finalizing the data cleaning process, we have a complete list of 88 mutual funds. These funds are all categorized as "active", only invest in equity, and lastly invest solely in multiple emerging market countries. As reflected in the table below, not all mutual funds in the sample have existed for the last 10 years.

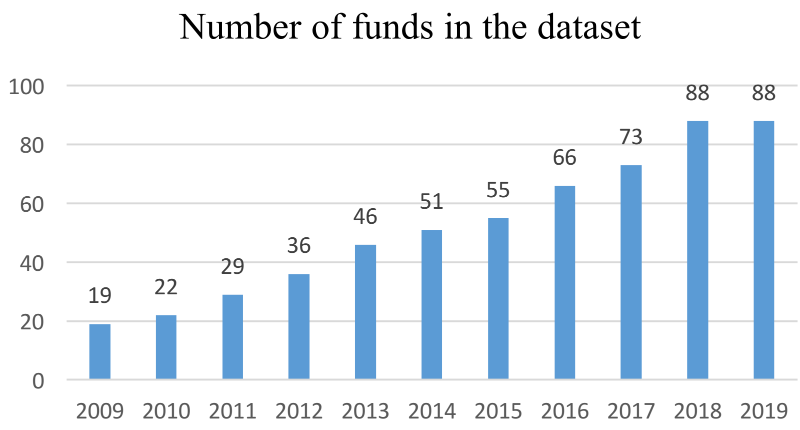

Figure 2: *Number of funds in the dataset*

Descriptive statistics for the activity metrics are included below. The average active share of 73.36% is well above the 60% threshold as set in Cremers & Petajisto (2009) for a mutual fund to be a "potential closet index fund". There are also relatively significant differences between mutual funds, as reflected in the between standard deviation of 11.38%. This is important because active share differences between funds is a requirement for active share to be an interesting parameter to study further. The relatively low within standard deviation of 5.31% implies that the mutual funds are rather persistent in how active they are, according to active share. Lastly, the average tracking error of 8.54% is above the 4-7% interval which Zephyr (2013) suggests include "most traditional mutual funds".

Summary statistics for Active Share and Tracking Error

	Mean	Standard deviation	Min	Max	Observations
Active Share (%)					
Overall	73.36	11.96	27.61	98.68	6050
Between		11.38	31.65	88.93	88
Within		5.31	44.99	96.12	T-bar = 68.75
Tracking Error (%)					
Overall	8.54	4.99	0	52.91	6050
Between		3	3.12	14.85	88
Within		3.91	2.37	52.13	T-bar = 68.75

Table 1: *Summary statistics for active share and tracking error*

5.2 Factor data

To assess mutual fund performance, we apply factor models with various risk factors. As far as we aware of, there is no existing database that include the factors we need for our factor models. Thus, as elaborated in the methodology chapter, the factors had to be calculated. Most factors were proxied by utilizing MSCI's vast number of indexes (MSCI, 2019), with inspiration from Fasano & Gallappo (2016).

We collect the factor data from a few different sources. All the MSCI Indexes are collected from MSCI's website, which contains a vast amount of different indexes (MSCI, 2019). The momentum and carry factor data were collected through Bloomberg. There are uncertainties as to how good our proxies for the risk factors are. This relates especially to our Carry and Momentum proxies, as we find it somewhat unclear as to how exactly these portfolios are constructed. Still, we believe that our proxies capture the effects that they are intended to, at least to a certain extent.

The 1-month U.S. bond yield was used to represent the risk-free rate and was collected from the U.S. Federal Reserves' website (Federal Reserve, 2019). The yield that we collect from this website is annualized, and consequently we divide it by 12 to calculate the monthly yield.

5.3 Biases and data weaknesses

There are some biases that may impact the results of our analyses. One such obvious bias is survivorship bias. The collection of funds in our database all exist as of 2019. It may very well be that in the time period that this paper investigates, there have been funds not included in our database that have ceased to exist due to underperformance. Thus, historical returns may be overestimated and risks underestimated (Fung & Hsieh, 2001).

Another relatively similar bias can occur due to the fact that not all the funds included in the database existed in all years. In 2009, only 19 funds of the 88 in the database existed. Years with fewer funds may include more uncertainty than more exhaustive years. Furthermore, with more observations in some years than others, aggregate results may be biased towards the years with more observations. We do however strive to account for this problem by including year dummies in regressions when relevant to control for time fixed effects, in addition to using rolling window regressions to calculate betas for each year.

A more ideal database would be one that builds from the same source, instead of multiple different sources. In this paper, data from Morningstar and Bloomberg were merged. Although we consider both sources credible, the collection and merging processes were time-consuming. For others to do a similar analysis and control our results, it would be ideal if the data gathering was a more concentrated process, preferably through one source. Although merging the data was done carefully, the merging and cleaning process is prone to human error.

While not a data weakness in itself, the way we filter the data limits the inference to count for only all-equity funds that invest in a multinational manner. Kacperczyk et al. (2005) argues that concentrated funds perform better than non-concentrated funds. Thus, an analysis with different scope than this paper could yield different results.

Data outliers can impact the results of empirical analyses. We decide not to winsorize the data as we do not have information that indicate that outliers are not valid datapoints, nor do we wish to remove outliers that may be sources of interesting information. Further, we believe that winzorizing the data would not have impacted the results significantly, given the very limited number of significant relationships and differences in this study.

6. Analysis

In chapter, we elaborate our analyses and present our results. We perform three different analyses, and start with the preliminary sub-analysis. Thereafter, we progress to the analysis that examines differences between truly active funds and closet indexers in a binary manner. Lastly, we treat activity as a scale and examine the relationship between mutual fund performance and activity.

6.1 Do some emerging markets mutual funds outperform the market consistently?

In the preliminary sub-analysis, we examine whether some emerging markets mutual funds outperform the market consistently. We review the mutual funds' performance across three metrics: pure returns (both pre- and post costs), Sharpe ratio and, most importantly, alpha. The motivation behind this chapter is to test our sub-hypothesis that astute mutual funds can utilize the (alleged) market inefficiencies in emerging markets to produce consistent and superior performance compared to the market.

How are the mutual funds' returns compared to the market?

In this analysis, we firstly examine what percentage of mutual funds have returns higher than that of the major ETFs in addition to testing whether the average mutual fund returns are statistically different from the average ETF returns. With a correlation coefficient of 0.995 and R^2 of 99% (as described earlier) with the MSCI Emerging Markets Index, the average return of the three major emerging markets ETFs represent a valid proxy for the market.

The annual average returns is calculated for each fund in every year. This return is then compared to the average return of the three major emerging markets ETFs. This comparison is done both pre costs (Figure 3) and post costs (Figure 4). For post cost, the net expense ratio is subtracted from the average annual return for both the mutual funds and the ETF average.

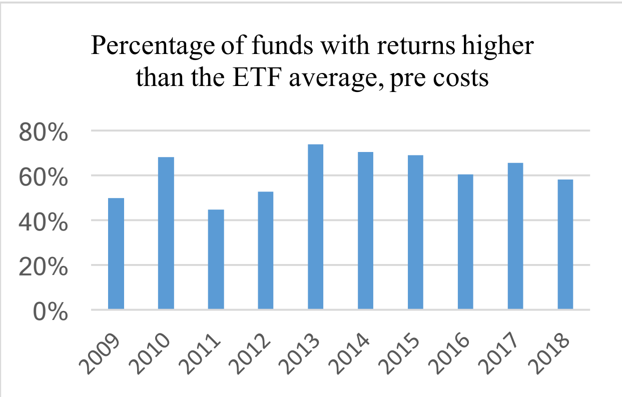

Figure 3: *Percentage of mutual funds with annual average pre cost returns that are higher than the ETF average (2009-2018)*

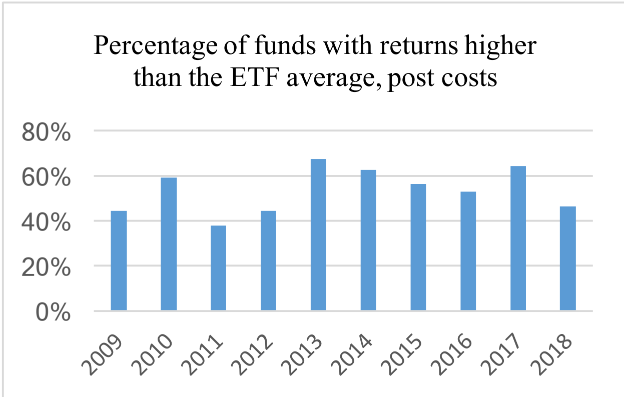

Figure 4: *Percentage of mutual funds with annual average post cost returns that are higher than the ETF average (2009-2018)*

On average, a majority of 61.4% mutual funds across all years in our dataset produced annual pre cost returns that were higher than the average of the three largest emerging markets ETFs. Here, we omit the year 2019 because it only covers three months. The average mutual fund return was higher than the average ETF return in all but one year. Post costs, an average of 53.6% of mutual funds outperformed ETFs. It should be noted, however, that the net expense ratio does not include sales commission fees or loads.

While figure 3 and figure 4 do depict that on average a majority of the mutual funds produce better returns than ETFs, they do not depict how large the return differences are, nor whether or not the differences are statistically significant. The average difference in monthly pre cost returns between mutual funds and the ETFs across all years is 0.139%. This is equal to an annualized difference of 1.68%. A t-test of differences between the mean monthly mutual fund returns and the monthly ETF returns reveals that the difference is indeed statistically significant, with a t-value of over 7. Post cost, the average monthly difference between mutual funds and ETFs is 0.066%, which when annualized equals 0.79%. The t-value is 3.3, rendering the post cost difference statistically different from zero as well.

How are the mutual funds' Sharpe ratio compared to the market?

While the mutual funds' returns are impressive compared to the ETF benchmark in this study in terms of pure returns, both before and after costs, a further analysis where risk is accounted for is required. The Sharpe ratio is a metric that compares returns to the associated risk (Investopedia, 2019). We perform a similar analysis as in the examination of return differences in how we calculate the percentage of funds that have superior Sharpe ratio compared to the market in each year. This analysis is then followed by a t-test that examines whether the differences in Sharpe ratio are statistically significant.

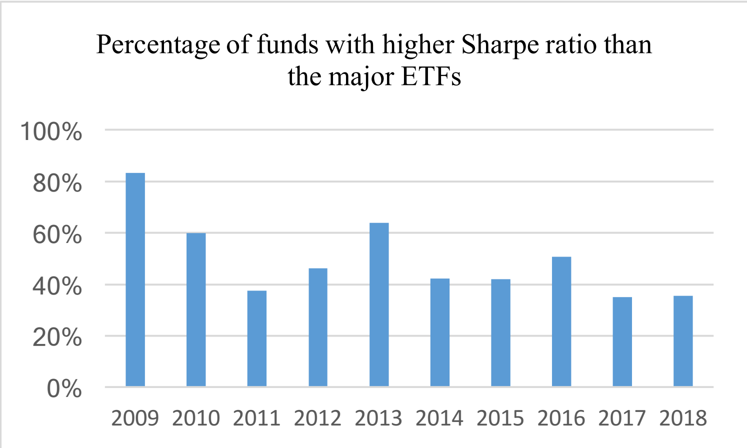

Figure 5: *Percentage of funds with higher Sharpe ratio than the major ETFs*

As figure 5 depicts, the year 2009 is an obvious outlier. In this instance, an outstanding 83% of mutual funds had superior Sharpe ratio than that of the ETFs. 2009 was a unique year as it included extreme returns. For instance, the EEM MSCI ETF had a return of 78.5% (MCSI, 2018). However, this year is followed by varied results in later years. Notably, the average percentage of mutual funds that have a higher Sharpe ratio than the ETF average across all years is 49.6%. Compared to the average percentage of funds that produced superior pure returns of above 60% depicted in figure 3, this is an indication that the mutual funds take on higher risk in their pursuit of beating their benchmark. The average standard deviation of the mutual funds' returns may be higher because the mutual funds are less diversified than the ETFs. For instance, the EEM MSCI ETF holds no less than 1136 different portfolio companies (MCSI, 2018).

The mean of the monthly Sharpe ratio difference between mutual funds and ETFs is -0.0037 and with a t-value of -0.33 the difference is not statistically significant. Thus, when adjusted for risk, the mutual funds and ETFs have performed comparatively in the 10-year time period.

Regression analysis

The final assessment of the performance of the mutual funds compared to the market is done through examining alpha. As previously mentioned, alpha can be considered as a measure of out- or underperformance, and is often used to measure whether fund managers possess skill, as in Fama and French (2010). Another benefit of examining factor model regression results is that we also can also to a certain extent infer something about the investment strategies of the mutual funds.

We follow the methodology as described earlier and conduct 88 regressions (one for each fund) for each of the factor models. The time period encompasses the entire sample period of ten years. The average results, where each fund is weighted equally, are summarized below in table 2.

Average OLS regression results for mutual fund excess returns (2009-2019)

	(1) CAPM	(2) Carhart	(3) CAPM Redux
Constant	-0.065***	-0.061***	-0.189***
	(0.19)	(0.18)	(0.20)
CAPM	0.951***	0.956***	1.042***
	(0.11)	(0.09)	(0.13)
SMB		0.052***	0.101***
		(0.15)	(0.16)
HML		-0.040	0.015
		(0.25)	(0.26)
UMD		-0.000	-0.020***
		(0.03)	(0.04)
Carry			0.446***
			(0.13)
Dollar			-0.111***
			(0.21)
No. funds	88	88	88
Adjusted R^2	0.91	0.92	0.92
	(0.06)	(0.06)	(0.06)

Table 2 - *Average OLS regression results for mutual fund returns minus the risk-free rate (2009-2019).*
This table depict the equally weighted average results from 88 regressions (one for every mutual fund) on the CAPM, Carhart and extended CAPM Redux models (see equation (4), (5) and (6)). Standard deviations of means are in parenthesis. Significance levels of 1%, 5% and 10% are denoted as ***,**, and *, respectively. The test for coefficient significance is conducted through two-sided t-tests, which tests whether the mean of the 88 coefficient estimates are equal to zero. The regressions are conducted with robust standard errors. The dependent variable is monthly mutual fund returns minus the risk-free rate (1 month U.S. treasury bill).
The factors (independent variables) are calculated inspired by the method of Fasano & Gallappo *(2016)*:
CAPM = MSCI Emerging Markets Index minus U.S. 1 month treasury yield,
SMB = MSCI Emerging Markets Small Cap. Index minus MSCI Emerging Markets Large Cap. Index,
HML = MSCI Emerging Markets Value Index minus MSCI Emerging Markets Growth Index,
UMD = Invesco's Emerging Markets Momentum ETF,
Carry = Bloomberg's Cumulative FX Carry Trade Index for 8 Emerging Markets,
Dollar = U.S. Treasury's Dollar Index

There are especially three results that are of interest. Firstly, the average alpha of the funds is negative and statistically different from zero. Thus, one can infer that the mutual funds on average perform worse than the market.

The second result that stand out is how high the average R^2 is. We observe how even with just the CAPM term in model (1), the R^2 is higher than 90%. The incremental increase in R^2 from adding the additional Carhart factors and the currency factors is abysmal (from 91% to 92%).

Thus, the variation of the mutual funds' returns can to a large extent be explained solely by variation in the MSCI Emerging Markets returns minus the risk-free rate.

Lastly, we can observe that although the incremental increase in R^2 is very low, the SMB, UMD, Carry and Dollar factors are all statistically different from zero in one or more models. The UMD factor is somewhat ambiguous, since it statistically significant in the CAPM Redux model, but not in the Carhart model. The CAPM factor is also significant and positive which tells us, quite unsurprisingly, that the mutual funds' returns are positively associated with the market return.

The average currency coefficients are both statistically significant. This suggest that currency effects do impact the returns of the mutual funds. That the dollar coefficient is negative makes sense from an intuitive standpoint: as the USD appreciates, the conversion of returns in local currency to returns in USD becomes less favorable.

Since the SMB factor is positive and statistically significant, it seems that the average mutual fund has a slightly a larger exposure to small capitalization stock than large capitalization stock. The UMD factor's sign is negative. For each percentage point increase in the momentum index´s monthly returns, the average mutual fund's monthly return decreases by 0.02%. This result somewhat difficult to interpret. With that being said, both the SMB and UMD coefficients are very low. This fact, combined with the abysmal incremental explanatory power, means that one should be careful in inferring too conclusively about these factors.

Table 3 below allows for a closer inspection of the regression results. The table depicts the number of funds that have alphas and factor coefficients that are statistically different from zero, and whether these differences are positive or negative.

Number of funds with statistically significant coefficients (2009-2019)

	Model (1): CAPM	
	Alpha	*CAPM*
Positive and p-value < 5%	1	87
Negative and p-value < 5%	7	0

	Model (2): Carhart				
	Alpha	*CAPM*	*SMB*	*HML*	*UMD*
Positive and p-value < 5%	1	87	2	10	0
Negative and p-value < 5%	11	0	16	25	6

	Model (3): CAPM Redux						
	Alpha	*CAPM*	*SMB*	*HML*	*UMD*	*Carry*	Dollar
Positive and p-value < 5%	0	0	0	19	0	0	1
Negative and p-value < 5%	21	86	21	22	7	78	9

Table 3 - *Number of funds with statistically significant coefficients.*

The table depict the number of coefficients that are significant for each factor and alpha out of the 88 regressions per model. The significance level is set to 5%. Thus, coefficients with a p-value below 5% are considered to be statistically significantly different from zero.

From table 3 we can observe how only one out the total sample of 88 mutual funds has a monthly alpha value that is both positive and statistically different from zero in model (1) and (2). This result illustrates what has become rather common and accepted knowledge in the world of finance: beating the market over a longer time-horizon is extremely difficult. It is also notable how there are many more mutual funds that have statistically negative alphas in the CAPM Redux model compared to the other models. This could suggest that some of the mutual funds' poor performance is unmasked in the CAPM Redux model by controlling for the currency factors.

There are 16 and 21 funds that have SMB-coefficients that are positive and statistically different from zero in the Carhart and CAPM Redux regressions, respectively. Thus, a percentage of around 18-24% of the mutual funds in the sample may follow a strategy that include investing in small-cap stocks, while almost none of the mutual funds in the sample seem to prefer large-cap stocks. The result for the HML factor is more mixed. Looking at the Carhart model results, 25 of the mutual funds seem to have a larger weight in low book-to-market stocks, whereas the opposite is true for only 10 mutual funds. In the CAPM Redux regressions, the number of regressions that yielded statistically significant and positive HML coefficients almost doubles to 19, whereas the number of negative HML coefficients remain almost the same. This could potentially suggest that high book-to-market companies are more impacted by currency effects than low book-to-market companies.

In sum, some of the mutual funds in the sample have strategies of allocating more or less of their portfolio to the included factors other than the CAPM factor, but most of the mutual funds do not and are only statistically correlated with the overall market.

Concluding remarks on mutual fund performance compared to the market

Through the three parts of this chapter we have examined how the mutual funds in the sample have performed in comparison to the market. Interestingly, the mutual funds did on average have higher returns than the market, both pre and post costs. However, once risk was adjusted for, through Sharpe ratio and alpha examination, there was no general outperformance. On the contrary, the mutual funds do on average underperform once risk is accounted for, according to the statically significant and negative average monthly alpha.

The fact that the *average* mutual fund underperforms the market gross of cost, as depicted by table 2, is somewhat surprising if one considers the concept of equilibrium accounting, as described in Fama and French (2010). According to this concept, if one active investor outperforms, another must underperform, rendering active investing a zero-sum game. However, our sample does not encompass all types of active investors. The fact that the average mutual fund underperforms in our sample may suggest that other types of active investors, for instance hedge funds or other types of mutual funds than included in our sample, outperform when compared to our sample and the market. Hedge funds may be able to utilize their opportunity to short-sell companies or trade in derivatives. More concentrated funds, for instance funds that only invest in one country, may be better able to thoroughly analyze their niche and gain an informational advantage, as opposed to our sample of mutual funds that must cover a multitude of different countries continuously.

The result that only *one* mutual fund managed to outperform the market over a 10-year period is not necessarily surprising given prior studies on the subject. We earlier mentioned that astute mutual fund managers may be able to utilize market inefficiencies in emerging markets to produce consistent superior risk-adjusted returns compared to the market. Based on our results, however, this does not seem to be the case, at least not for our sample of funds. In sum, broad market ETFs such as the Vanguard FTSE Emerging Markets ETF seem to be a perfectly viable alternative for risk-neutral retail investors.

6.2 Do actively managed funds outperform closet indexers in emerging markets?

With our sub-analysis conducted, we now turn to the first of our main analyses. Here, we examine whether or not truly active mutual funds outperform closet indexers in emerging markets. Using Cremers & Petajisto's (2009) threshold for closet indexing, the funds are defined as either truly active or as potential closet indexers. The threshold used by Cremers & Petajisto (2009) to separate these two types of mutual funds is 60%, hence any mutual funds with an average active share below 60% are considered closet indexers. As earlier mentioned, the argumentation behind the 60% threshold is somewhat subjective and is supposed to be used as a rule-of-thumb. Cremers & Petajisto (2009) examine the U.S. market, and it can be argued that other thresholds for other markets are more suitable. With emerging markets being a large umbrella of multiple markets with a vast range of investment options, there could be merit for recommending a higher threshold. With the vast investment space available, achieving a higher active share may be easier for funds investing in emerging markets rather than markets that are smaller, such as national markets. For this reason, we also conduct an examination where we set the threshold to 70%. In later chapters, considering active share as a scale will be utilized to analyze the matter even more thoroughly. For now, we take a binary approach.

The rest of this chapter proceeds as follows. We begin by examining how active the funds in our sample are, according to active share and tracking error. Thereafter, we examine whether there is statistical difference in performance between the truly active mutual funds and closet indexers in our sample by using Mann-Whitney U-tests.

Active Share

We first examine how active the mutual funds in our sample are, according to active share. Each fund is placed in an active share bracket based on its average active share, as depicted in figure 6 below.

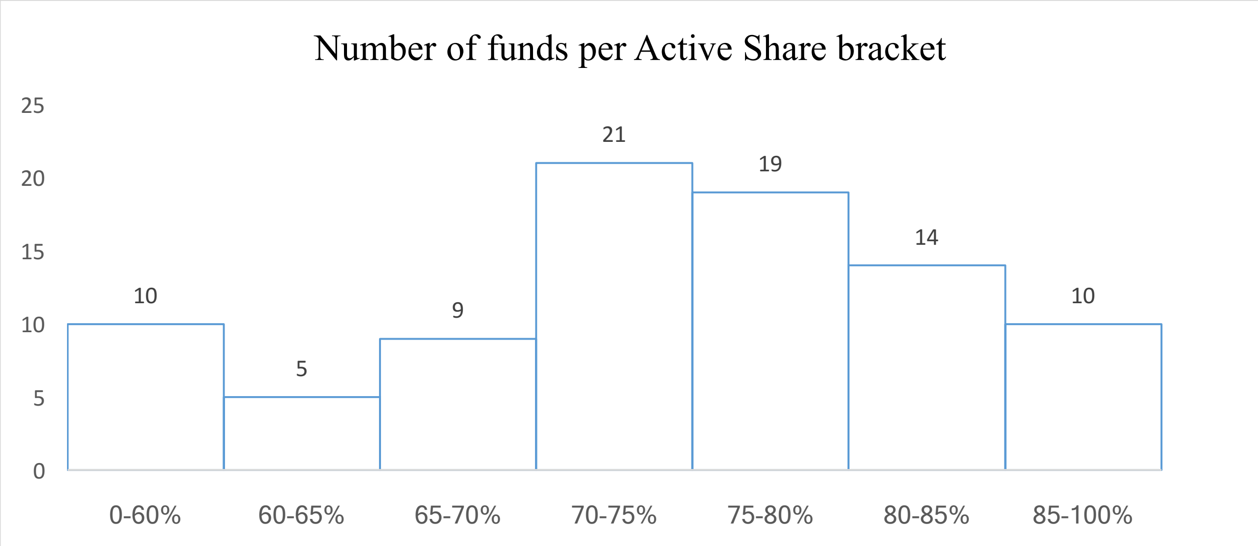

Figure 6: *Histogram of number of funds per Active Share bracket*

In our dataset, 10 of the 88 funds have had an average active share below the 60% threshold over the past 10 years. Notably, our results are quite similar to the U.S. market in 2015, as presented by Cremers & Pareek (2015). That year the percentage was slightly above 10%, almost equal to this study. On the other hand, the percentage of closet indexers in our sample is vastly different from the Norwegian market. Hovstad & Langeland (2018) found that 13 out of 21 funds Norwegian funds investing in the Norwegian stock market could be categorized as closet indexers in the time period 2008-2018. Furthermore, Cremers & Curtis (2016) find that for example, in Sweden, 50% of assets are invested in closet index funds, 58% in Poland and 44% in Sweden. Though invested assets are not necessarily equal to number of funds, we perceive it as likely that these numbers give an indication of differences between countries.

If we increase the threshold of closet indexing to 70%, 24 funds (27%) are included as closet indexers.

Tracking Error

While this paper's main emphasis is on active share as a measure of the degree of active fund management, the more traditional metric tracking error can allow for a further substantiation of the analysis. Zephyr (2013) notes how "most traditional active managers have tracking errors around 4%-7%". Using this interval, we can examine how active emerging markets mutual funds are in practice according to the funds' tracking error.

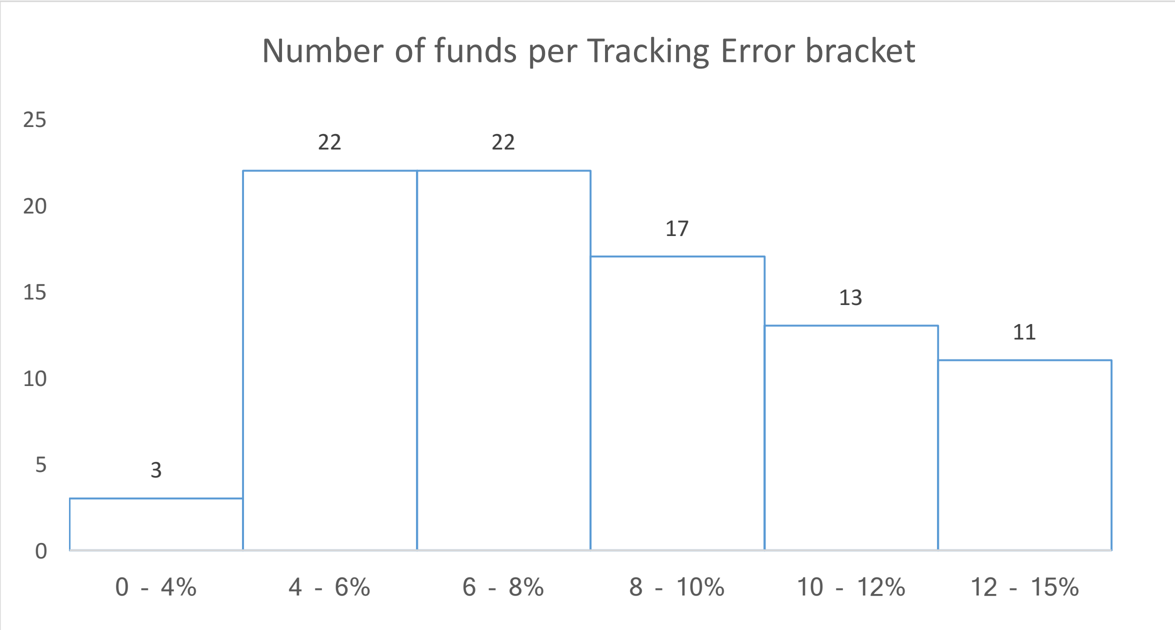

Figure 7: *Histogram of number of funds per Tracking Error bracket*

As depicted in figure 7, the number of mutual funds with an average tracking error below 4% is very low, which in turn means that the vast majority of funds in our sample have an average tracking error higher than that of "most traditional mutual funds". This result can be interpreted in multiple different manners. It can very well be a substantiation of the results in figure 6 that indicate that the degree of activity is high for funds investing in emerging markets and that there are very few potential closet indexers. On the other hand, the set threshold may just be too low for emerging markets. Further, the results can also potentially indicate that mutual funds investing in emerging markets are especially active in the "factor bets" part of active management. As mentioned, Cremers and Petajisto (2009) describes how active management can be separated into two parts: stock selection, which active share is a proxy for, and factor bets, which is proxied by tracking error.

Do active funds outperform closet indexers?

Having documented that there are some, but few, mutual funds in our sample that can be defined as potential closet indexers, we now turn to examine whether such funds perform differently from truly active funds. Following the 60% threshold explained in section 6.2, we divide our fund into two groups and compare their performance over the last 10 years. In addition, we do the same analysis with a 70% threshold. Table 4 below depicts the group averages of monthly gross and net returns, monthly Sharpe ratios, and lastly gross and net alphas.

Performance comparison – Closet indexers versus truly active funds

	Closet indexers (Active share < 60%)	Truly active funds (Active share > 60%)	Closet indexers (Active Share < 70%)	Truly active funds (Active Share > 70%)
Gross returns	0,352	0,492	0,443	0,506
Net of costs	*0,268*	*0,365*	*0,354*	*0,354*
Sharpe	0,053	0,055	0,051	0,056
CAPM Alpha	-0,057	-0,066	-0,093	-0,055
Net of costs	*-0,132*	*-0,166*	*-0,178*	*-0,156*
Carhart Alpha	-0,325	-0,333	-0,346	-0,327
Net of costs	*-0,399*	*-0,433*	*-0,430*	*-0,429*
CAPM Redux Alpha	-0,172	-0,192	-0,205	-0,184
Net of costs	*-0,247*	*-0,291*	*-0,289*	*-0,285*

Table 4: *Average performance measures for truly active mutual funds and closet indexers.*

Looking exclusively at average returns, funds with a higher active share (active share > 60%) have performed better over the past 10 years than closet indexers (active share < 60%), with a monthly difference of 0.14%. If we raise the limit to 70%, the outperformance in average returns is slightly above 0.06% monthly. However, the mean differences are not significantly different from zero when running a Mann-Whitney U-test on the data. The results remain consistent through all performance metrics, also net of costs. The uncertainty is high since we have so few mean observations of closet indexers (10). A larger sample of funds would in this instance reduce uncertainty. Potentially, a larger sample could yield the mean difference of 0.14% significant, but it is also possible that a larger sample would entail a convergence of means between the two groups.

In examining Sharpe differences, we observe that the difference in performance is now dwindled into a monthly difference of 0.0024% and 0.0054% respectively (60% and 70%), with funds of larger active shares still performing better. This small difference is also insignificant when tested with a Mann-Whitney U-test. We observe no different conclusion when we account for the costs of the investment options.

There are neither no statistical differences for alphas between the groups. All average alphas in both groups are negative. This coincides with the results from our sub-analysis.

Concluding remarks on the binary analysis

This section of the analysis is in line with the results and conclusions from the sub-analysis. There are no statistical return differences between truly active funds and potential closet indexers in our sample. The conclusion is also the same if the ceiling for being considered a closet indexer is raised to 70%. This conclusion is consistent through risk adjustment and remains steady when applying common market factors such as CAPM and Carhart four-factor model. The results do neither change when the models are considered net of cost. It should however be noted that due to the low number of funds in our sample being closet indexers, the conclusion is somewhat impacted by uncertainty. The results are not in line with Cremers & Petajisto (2009). They found that the funds with the highest active share significantly and with persistence outperformed their benchmark by 1.51%-2.4% per year before costs and 1.13%-1.15% after costs. Furthermore, they also found that the non-index funds with low active share underperformed their benchmark by up to -0.63% per year. After costs they perform even worse, underperforming their benchmarks by -1.42% to -1.83% per year.

6.3 Can the degree of active fund management explain mutual fund returns?

In the prior analysis, we viewed the degree of activity as binary. In the following, we treat activity as a scale. The structure of this analysis follows the same as earlier: we first examine differences in pure returns, followed by Sharpe and alpha differences. In order to examine these differences, we use a specter of regressions.

We start by examining regression models where the dependent variable is fund returns.

Association between mutual fund gross returns and degree of activity (2009-2019)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Active share	-0.008*		-0.006	-0.002	-0.081	0.003	0.003	0.003
	(0.004)		(0.004)	(0.029)	(0.086)	(0.011)	(0.011)	(0.011)
Tracking error		-0.019***	-0.018***	0.058***	-0.185***	0.055***	0.048***	0.048***
		(0.006)	(0.006)	(0.013)	(0.039)	(0.010)	(0.010)	(0.010)
Active share^2				-0.00003	0.001	-0.00004	-0.00004	-0.00004
				(0.0002)	(0.001)	(0.0008)	(0.0001)	(0.0001)
Tracking error^2				-0.002***	0.0005	-0.0023***	-0.0021***	-0.002***
				(0.0004)	(0.001)	(0.00034)	(0.00033)	(0.0003)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Fund fixed effects	Yes	Yes	Yes	Yes	Yes	No	Yes	No
Index	0.937***	0.935***	0.935***	0.936***		0.936***	0.946***	0.946***
	(0.004)	(0.004)	(0.004)	(0.004)		(0.004)	(0.004)	(0.004)
Constant	1.246***	0.916***	1.370***	0.981	12.62***	0.936***	-0.043	-0.043
	(0.442)	(0.330)	(0.444)	(1.142)	(3.378)	(0.374)	(0.386)	(0.386)
Observations	6,050	6,050	6,050	6,050	6,050	6,050	6,050	6,050
Adjusted R2	0.904	0.904	0.904	0.905	0.163	0.905	0.904	0.904

Table 5: *Association between mutual fund gross returns and degree of activity (2009-2019).*
Robust standard errors are in parenthesis. Significance levels of 1%, 5% and 10% are denoted as ***,**, and *, respectively. The dependent variable is monthly mutual fund returns. Active share is measured at the start of the month, whereas tracking error is the average tracking error of the same month.

We observe in table 5 how active share is only associated with mutual fund returns in model (1). The tracking error coefficient, on the other hand, is statistically significant in all five models. Interestingly, the coefficient of *Tracking error* is negative in model (2) and (3), but positive when *Tracking error*^{2} is introduced in the other models, with the exception of model (5). Tracking error^2 is negative in all models where it is included. Based upon these results, we can infer that it seems the relationship between returns and tracking error is not linear - some tracking error is associated with better returns, but very high levels of tracking error leads to a negative relationship.

Using the specific coefficient estimates, we can calculate the optimal level of tracking error. We base our calculation on model (4) since this model includes both time and fund fixed effects and the index returns. The level of tracking error that is associated with the highest mutual fund return is around 14.5%, which is approximately 6% above the average sample mutual fund tracking error. This optimal level of 14.5% is on average associated with an incremental positive monthly return of 0.42%. After the level of tracking error reaches higher than around 29%, the relationship between tracking error and mutual fund returns becomes negative. Naturally, there is a high level of uncertainty in these estimates, and the main takeaway is that investors should, according to model (4), avoid those mutual funds that have a level of tracking error that is in either tale of the distribution.

It should be noted that while 7 out of 8 of the models have an impressive R^2 of over 90%, the vast majority of this explained variation comes from including the MSCI Emerging Markets Index and the yearly dummies. The effect of excluding the MSCI EM Index is reflected in the R^2 of 17% in model (5). Because of the abysmal incremental explanatory power from including active share and tracking error, investors should certainly not base their investment decisions solely on these metrics.

Next, we turn to examining the relationship between the mutual funds' degree of activity and their Sharpe ratio.

Association between mutual fund Sharpe ratios and degree of activity (2009-2019)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Active share	0.00004		0.0001	0.003	0.0001	0.001	0.003	0.001
	(0.0003)		(0.0003)	(0.002)	(0.004)	(0.001)	(0.002)	(0.001)
Tracking error		-0.001**	-0.001**	-0.002*	-0.014***	-0.001	-0.004***	-0.002*
		(0.0004)	(0.0004)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Active share^2				-0.00002	0.00000	-0.00000	-0.00002	-0.00000
				(0.00001)	(0.00003)	(0.00001)	(0.00002)	(0.00001)
Tracking error^2				0.00003	0.0002***	0.00000	0.00004	-0.00001
				(0.00003)	(0.0001)	(0.00003)	(0.00003)	(0.00003)
Year dummies	0.133***	0.128***	0.127***	0.127***	-0.134***	0.131***		
	(0.011)	(0.011)	(0.012)	(0.012)	(0.022)	(0.011)		
Fund fixed effects	0.014	0.015	0.016	0.017	0.045		0.018	
	(0.025)	(0.025)	(0.025)	(0.025)	(0.048)		(0.026)	
Index	0.041***	0.041***	0.041***	0.041***		0.041***	0.041***	0.041***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)		(0.0003)	(0.0003)	(0.0003)
Constant	-0.067**	-0.050**	-0.060*	-0.162*	0.333**	-0.094***	-0.071	0.017
	(0.033)	(0.025)	(0.033)	(0.086)	(0.164)	(0.030)	(0.088)	(0.030)
Observations	6,050	6,050	6,050	6,050	6,050	6,050	6,050	6,050
Adjusted R^2	0.767	0.767	0.767	0.767	0.154	0.768	0.751	0.751

Table 6: *Association between mutual fund Sharpe ratio and degree of activity (2009-2019).*

Robust standard errors are in parenthesis. Significance levels of 1%, 5% and 10% are denoted as ***,**, and *, respectively. The table depict pooled OLS and fixed effects regression results, where the dependent variable is monthly Sharpe ratio. *Active share* is measured monthly at the start of each month, whereas *Tracking error* is the average tracking error in a month.

We observe in table 6 how there is no significant relationship between active share and the mutual funds' Sharpe ratio. Again, the tracking error coefficients are statistically significant. This time, however, the relationship seem to be solely negative, apart from in model (5) where the squared tracking error is statistically significant and positive. This may suggest that while increasing the tracking error somewhat can lead to higher returns, as reflected in table 5, this additional return is outweighed by the additional risk than is taken.

Lastly, we examine the relationship between the degree of mutual fund activity and alpha. Note that the regression below in table 7 only depict the relationship between the mutual funds' *Carhart* alpha values and the mutual funds' degree of activity. The regressions for CAPM alphas and CAPM Redux alphas are included in the Appendix since they depict very similar results (tables 15 and 17).

Association between mutual fund Carhart alpha and degree of activity (2009-2019)

	(1)	(2)	(3)	(4)
Average active share	-0.001		-0.0003	-0.012
	(0.002)		(0.002)	(0.013)
Average active share^2				0.0001
				(0.0001)
Average tracking error		-0.004	-0.004	0.054
		(0.007)	(0.007)	(0.039)
Average tracking error^2				-0.003
				(0.002)
Constant	-0.016	-0.027	-0.007	0.137
	(0.126)	(0.056)	(0.127)	(0.424)
Observations	88	88	88	88
Adjusted R^2	-0.010	-0.007	-0.018	0.001

Table 7: *Association between Carhart alphas and degree of activity (2009-2019).*

Robust standard errors are in parenthesis. Significance levels of 1%, 5% and 10% are denoted as ***,**, and *, respectively. The dependent variable is all the sample mutual funds' Carhart alpha over the entire time period (2009-2019). Average active share and Average tracking error are each funds' average across the same time period.

From table 7 we observe that the active share and tracking error coefficients are not statistically significant in any of the models, nor when squared. Thus, the degree of mutual fund activity can not explain out- or underperformance.

As mentioned in the methodology chapter, we conduct rolling window regressions in case the coefficients are time-variant. The results are depicted in the Appendix. We can observe that the coefficients vary somewhat between years, but that the conclusion remains unchanged – in the vast majority of years, the coefficients for active share and tracking error in all models are not statistically different from zero.

Concluding remarks on the scale analysis

Based on the regression results in table 5, 6 and 7, we can reject the hypothesis that emerging markets mutual fund performance is positively related to degree of active fund management. The result is contradicting to the findings of Cremers & Petajisto (2009) where active share proved positively associated with superior performance. Arguably, due to the supposed market inefficiencies in emerging markets, one would expect to achieve similar results for mutual funds in emerging markets.

Both table 5 and 6 did yield statistically significant *tracking error* coefficients. It should however be noted that adjusted R^2 in models all models is extremely low, meaning that variation in the average active share and tracking error of a mutual fund can only explain an abysmal degree of variation in the mutual funds' alpha levels. In sum, retail investors should not base their investment decisions upon active share and tracking error, at least not for funds similar to those in our sample.

7. Conclusion

In this thesis, we investigate whether or not there is a positive relationship between performance and the degree of fund activity for mutual funds that invest in emerging markets in the time period 2009-2019. Our hypothesis builds on the findings of Cremers & Petajisto (2009), where a positive relationship between performance and the activity metric Active Share was uncovered in the U.S. stock market. To test our hypothesis, we perform two separate main analyses on the basis of a sample consisting of 88 emerging markets mutual funds gathered from Morningstar and Bloomberg. In addition to our two main analyses, we also perform a sub-analyses of whether or not there exists mutual funds that are able to outperform the market consistently.

We find that a majority of the sample mutual funds produce average monthly returns that are higher than that of the market. The annualized average differences between mutual funds and the market are 1.68% and 0.79% gross- and net-of-costs, respectively. A t-test, testing whether the mean difference is equal to zero, depicts that the results are indeed statistically significant. When risk is accounted for through examining Sharpe Ratio and Alpha, there are however no significant differences between mutual funds and the market. This is an indication that the mutual funds take on more risk than the market, perhaps in their pursuit of beating their benchmark. Through factor models we find that some of the mutual funds in the sample are more exposed to various factors than other mutual funds, which indicates some divergence in the investment strategies that the mutual funds follow. For example, 16 out of the 88 mutual funds show statistically significant and positive exposure to the SMB-factor in the Carhart model, indicating a favoritism of small-capitalization stocks.

In the first of the two main analyses, we investigate whether there are significant performance differences between "potential closet indexers" and those mutual funds that are truly active. This distinction is made by using an Active Share threshold of 60%. The mutual funds with an active share below this threshold are defined as potential closet indexers, whereas those funds with active share higher than the threshold are defined as truly active. We find that there is no statistically different performance between potential closet indexers and truly active mutual funds. This conclusion is made on the basis of Mann-Whitney tests for differences in returns, Sharpe Ratios and Alphas between the two groups.

In the second of the two main analyses, we employ regressions with performance metrics as the dependent variable, and Active Share and Tracking Error, along with controls, as independent variables. This approach tests whether there is a linear (or non-linear) relationship between the performance metrics and the measurements of the degree of activity. The results depict that Active Share and Tracking Error cannot explain differences in performance.

Considering the results in the two main analyses, we reject the hypothesis that there is a positive relationship between emerging markets mutual funds' performance and their degree of active fund management. It should be noted that this conclusion is limited to the nature of the mutual funds in our database, which consists of all-equity mutual funds that invest in a wide range of emerging market countries. The results are different from the findings of Cremers & Petajisto (2009). This may be due to several reasons. Different market conditions, or differences in the type of mutual fund data or calculation methods are among plausible explanations.

For further research, we believe conducting a similar approach to hedge funds or more concentrated markets could prove interesting. Hedge funds, with their ability to short-sell stocks and trade derivatives, can possibly utilize the alleged market inefficiencies in emerging markets to their advantage. In this paper, we solely examined mutual funds that invest in multiple countries. The results could potentially be different for mutual funds that are more concentrated in their investment strategies, for instance because a mutual fund with local presence that only invests in one country could have an informational advantage over multinational funds without local presence. After all, Kacperczyk et al. (2005) find that more concentrated mutual funds outperform less concentrated mutual funds.

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Appendix

Time-varying coefficients from rolling window regressions

The figures below depict the time-varying coefficients from different sets of regressions that relate to section 6.3. The lines in the figures depict each coefficient's confidence interval. We observe that the vast majority of year-specific confidence intervals overlap with zero along the y-axis. In such instances, the coefficient is not different from zero in a statistically significant manner.

Time-varying coefficients from regressions with monthly returns as dependent variable

The 10-year equivalent of these regressions are summarized in table 5. The rolling window regressions include mutual fund fixed effects and index returns.

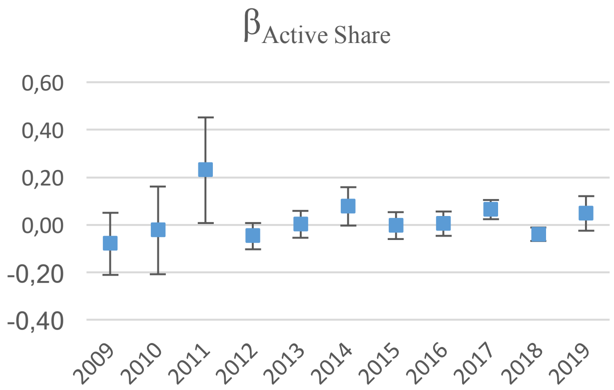

Figure 8: *Beta active share, returns regression.*

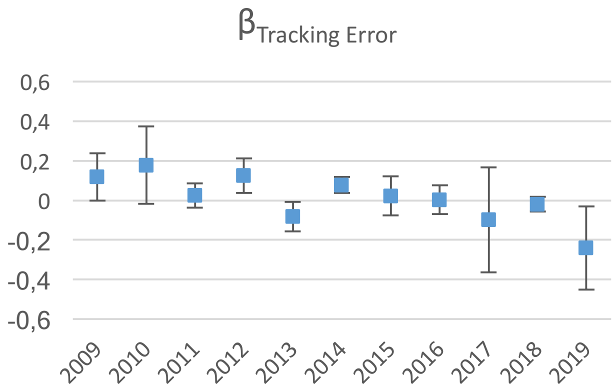

Figure 9: *Beta tracking error, returns regression.*

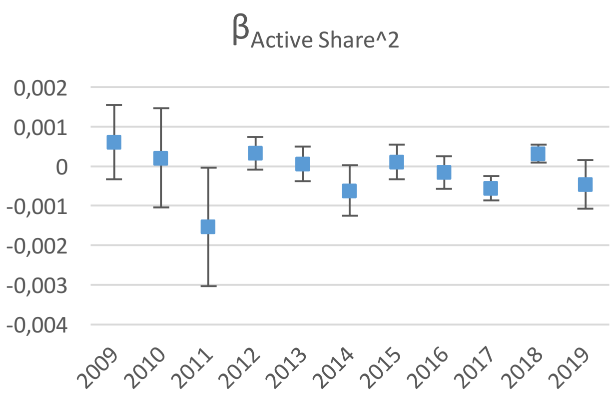

Figure 10: *Beta active share^2, returns regression.*

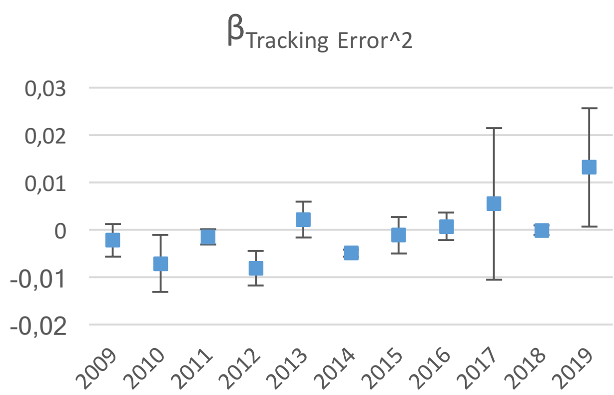

Figure 11: *Beta tracking error^2, returns regression.*

Time-varying coefficients with monthly Sharpe ratios as the dependent variable

The 10-year equivalent of these regressions are summarized in table 6. The rolling window regressions include mutual fund fixed effects and index returns.

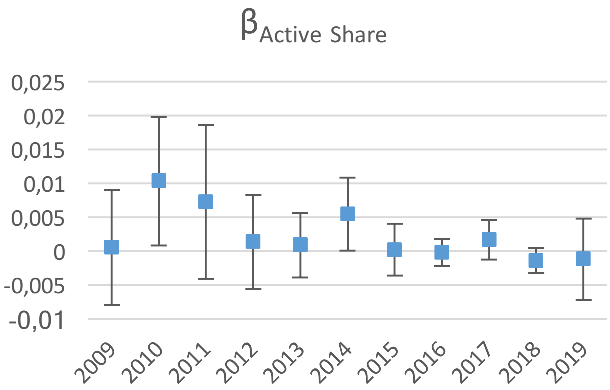

Figure 12: *Beta active share, Sharpe regression*

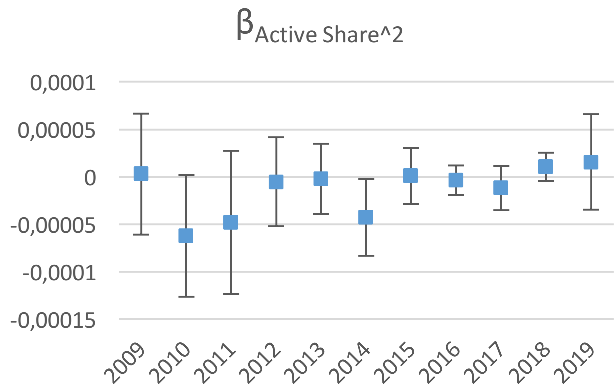

Figure 13: *Beta active share^2, Sharpe regression.*

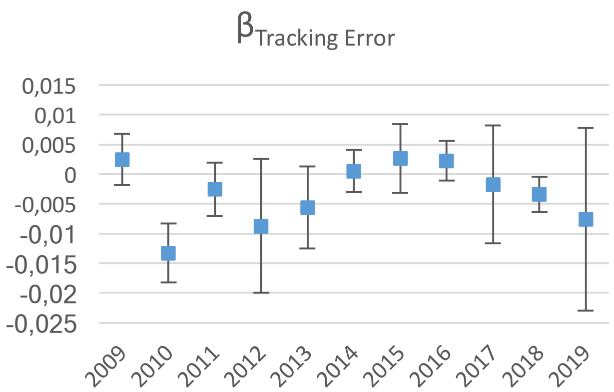

Figure 14: *Beta tracking error, Sharpe regression.*

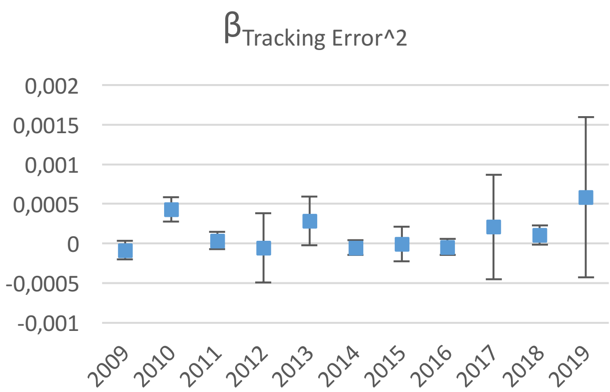

Figure 15: *Beta tracking error^2, Sharpe regression.*

Time-varying coefficients with Alpha as the dependent variable

The 10-year equivalent of these regressions are summarized in table 7. All the figures are regressions with Carhart gross alphas as the dependent variable.

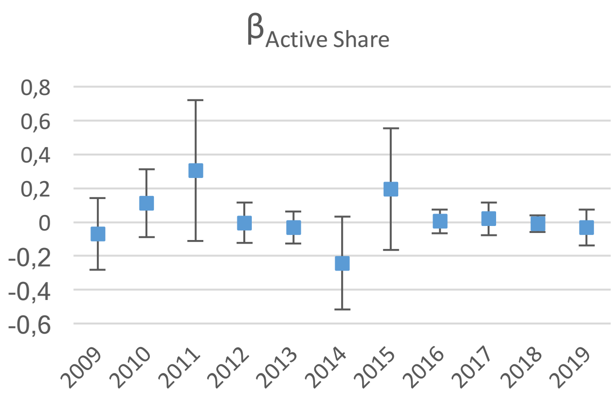

Figure 16: *Beta active share, Carhart regression.*

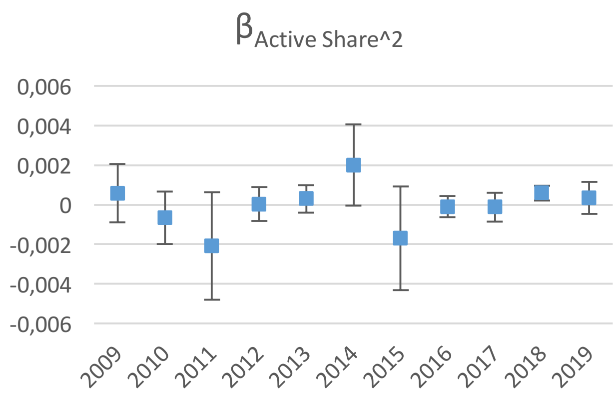

Figure 17: *Beta active share^2, Carhart regression*

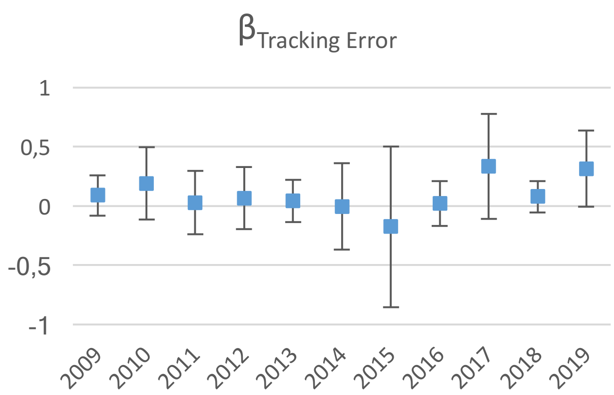

Figure 18: *Beta tracking error, Carhart regression.*

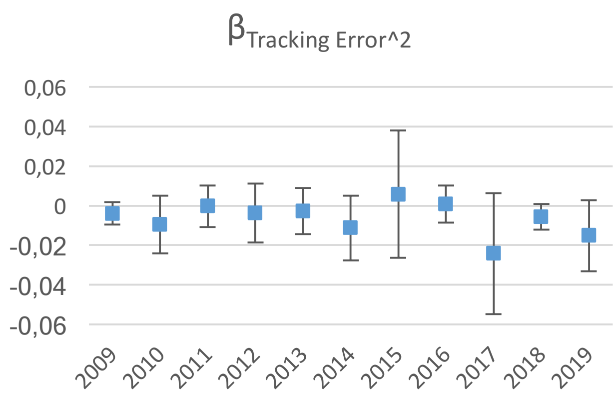

Figure 19: *Beta tracking error^2, Carhart regression.*

Econometric Assumptions

Autocorrelation

In the individual fund regressions that form the basis of table 2, some of the regressions are impacted by the presence of autocorrelation. This was uncovered using Durbin-Watson tests. Specifically, 3, 4 and 6 different funds showed signs of autocorrelation in the CAPM, Carhart and CAPM Redux regressions, respectively. We test the implication of this autocorrelation for the results by transforming the coefficients, using the FGLS method (Cochrane-Orcutt estimates) to remove the autocorrelation.

Below in table 8-10 are the OLS and FGLS coefficient estimates along with significance levels. In sum, we see that transforming the variables does not lead to large changes in significance level for any factors in any of the regressions where autocorrelation is present. This means that number of funds with statistically significant coefficients remain the same (see table 3), independent of whether we use OLS or FGLS for the fund regressions where autocorrelation is present.

However, we also observe how the alpha values change dependent on the method used. In the analyses that follow after the sub-analysis, we use the FGLS alphas for the fund regressions that were impacted by autocorrelation.

Cochrane-Orcutt estimates for the CAPM model

Fund number	Method	Alpha	CAPM
47	OLS	-0.023	1.057***
	FGLS	-0.24	1.074***
64	OLS	-0.007	0.801***
	FGLS	-0.236	1.074***
81	OLS	0.037	1.044***
	FGLS	-0.012	1.013***

Table 8: *Cochrane-Orcutt estimates the CAPM model*

Cochrane-Orcutt estimates for the Carhart model

Fund number	Method	Alpha	CAPM	SMB	HML	UMD
16	OLS	-0.264***	0.937***	0.096*	0.02	-0.01
	FGLS	-0.265**	0.937***	0.111*	0.018	-0.01
64	OLS	-0.048	0.811***	0.018	0.018*	-0.022
	FGLS	-0.087	0.798***	-0.009	0.169*	-0.017
76	OLS	-0.031	0.982***	0.144*	-0.034	-0.012
	FGLS	-0.117	0.948***	0.123*	-0.053	-0.044
81	OLS	-0.006	1.050***	-0.111	0.204**	0.034
	FGLS	-0.034	1.017***	-0.113*	0.217**	-0.002

Table 9: *Cochrane-Orcutt estimates the Carhart model*

Cochrane-Orcutt estimates for the extended International CAPM Redux model

Fund number	Method	Alpha	CAPM	SMB	HML	UMD	Carry	Dollar
16	OLS	-0.374***	0.941***	0.112*	-0.023	-0.015	0.594***	-0.149
	FGLS	-0.375**	0.929***	0.125*	-0.004	-0.022	0.601***	-0.168
19	OLS	-0.221*	0.888***	-0.007	0.353***	-0.028	0.654***	0.025
	FGLS	-0.182	0.875***	-0.001	0.344***	-0.039	0.666***	-0.024
64	OLS	-0.064	0.824***	0.025	0.137	-0.068*	0.449***	-0.473**
	FGLS	-0.103	0.805***	-0.013	0.148*	-0.061*	0.453***	-0.486**
73	OLS	0.009	1.173***	0.555***	-0.057	-0.036	0.521***	-0.213
	FGLS	0.029	1.200***	0.601***	-0.027	-0.043	0.479***	-0.158
76	OLS	-0.058	1.033***	0.221*	-0.017	-0.046	0.363***	-0.174
	FGLS	-0.150	0.967***	0.191*	-0.034	-0.091*	0.371***	-0.099
81	OLS	-0.208	1.172***	-0.100	0.128	0.031	0.500***	-0.038
	FGLS	-0.205	1.078***	-0.102	0.178*	-0.011	0.561***	-0.082

Table 10: *Cochrane-Orcutt estimates for the extended International CAPM Redux*

No perfect multicollinearity

As earlier noted, Allison (2012) argues that VIF-values over 2.5 indicate possible multicollinearity. From table 11 below, we thus conclude that multicollinearity is not a problem in our dataset.

Variance Inflation Factor

Factor	VIF	1/VIF
Carry	2.23	0.45
CAPM	1.9	0.53
Dollar	1.68	0.59
UMD	1.41	0.71
SMB	1.1	0.91
HML	1.07	0.93
Mean VIF	1.56	

Table 11: VIF test for factors

Correlation matrix for risk factors

	CAPM, USD	CAPM, local	SMB	HML	UMD	Carry	Dollar
CAPM, USD	1						
CAPM, local	0.929	1					
SMB	-0.13	-0.154	1				
HML	-0.849	-0.058	0.193	1			
UMD	0.066	0.085	0.109	0.012	1		
Carry	0.777	0.687	-0.201	-0.17	0.028	1	
Dollar	-0.384	-0.384	-0.035	0.012	-0.508	-0.418	1

Table 12: *Correlation matrix for risk factors*

List of mutual funds in the sample

Fund name	ISIN	Fund name	ISIN
AAMMF Numeric Emerg Mkt Eq I USD	LU1181318780	Jyske Invest Emerging Market Equity CL	DK0016260193
Acadian Emerg Mkts Eq II C USD Ins Acc	IE00BH7Y7M45	Lazard Developing Markets Eq A Acc USD	IE00B4W4B049
Acadian Emerg Mkts Eq UCITS D USD HybAcc	IE00BYQDD901	Lazard Emerging Mkts Eq Advtg EA Acc USD	IE00BFX4D935
Acadian Emerg Mkts Mgd VolEq UCITS C USD	IE00BYZHSC13	Legg Mason QS Em Mkts Eq A USD Acc	IE00B19ZCC84
Acadian Sust EMkts Eq EF Fuel UCITS BUSD	IE00BYX4R619	LO Funds Emerg Rspnb Eq Enh USD SA	LU0293417530
Allianz Best Styles EM Equity RT USD	LU1698897672	Magna Emerging Markets Z USD Acc	IE00BDHSR951
Allianz GEM Equity High Div AMg USD	LU1282651048	Man Numeric Emerging Markets Eq I USD	IE00BTC1NF90
Allianz Glbl Emerg Mkts Eq A USD	IE0002488884	MDPS TOBAM AntiBench Emerg Mkts Eq A	LU1067853769
Am Century SICAV - Em Mkt Eq Ax USD Acc	LU0968597913	Merian Global Emerging Mkts A USD Acc	IE00B53SVZ72
Amundi Fds Eq Emerging Cnsrv FU-C	LU0945154598	Multipartner CEAMS Eqlty EmMkts Eq B USD	LU0519702418
AQR Emerging Equities UCITS A1	LU0977235596	Neuberger Berman Em Mkts Eq USD InstlAcc	IE00B3NBSZ12
Artemis Fds (Lux) Global EM FI USD Acc	LU1893898095	Neuberger Berman EM Sust Eq USD I Inc	IE00BZ3CFV39
Artemis Global Emerging Mkts I Acc USD	GB00BW9HL579	NN (L) Emerg Mkts Hi Div I Cap USD	LU0799805873
AS SICAV I Em Mkts Eq A Acc USD	LU0132412106	Nordea 1 - Stable Emerg Mkts Eq BI USD	LU0637344622
AS SICAV I Em Mkts Eq Ethic G Acc USD	LU1581388169	Nordea 2 - EM Enhanced Equity BI USD	LU0994675097
Aubrey Global Emerging Markets Opps IC1$	LU1177490023	Parvest Equity Wld Emerg Low Vol X C	LU0925123712
Aviva Investors EM Eq Inc A USD Acc	LU0274940138	PIMCO GIS RAE Em Mkts Instl Acc	IE00BWX4BS70
AXA Rosenberg Glb Em Mkts Eq Alp B $ Acc	IE00B101K096	PineBridge Global Emerg Mkts Foc Eq A	IE00B0JY6N72
AXAWF Fram Emerging Markets M Cap USD	LU0451400674	Principal Origin Glb Em Mkts I Acc USD	IE00B4PCVC77
BCV Global Emerging Equity C	CH0142917118	Quoniam Fds Sel EmMktsEqsMnRsk USD I acc	LU0612194984
C WorldWide Emerging Markets 1A	LU0086737482	RAM (Lux) Sys Emg Mkts Equities IP USD	LU0704154458
Capital Emerging-Markets USD	TW000T1605B0	River & Mercantile EM ILC Eq EB USD	LU1692110783
Cathay Emerging Markets USD	TW000T3728U8	Robeco Emerging Opportunities Eqs I $	LU1215394039
CSIF (Lux) Equity Em Mkts Fdmtl DB USD	LU0760136324	Robeco Emerging Stars Equities FL $	LU1193126049
CSIF (Lux) Equity Em Mkts Min Vol DB USD	LU1326428775	Robeco QI EM Active Equities I $	LU0858455784
Cullen EM Hi Div I2 USD Ins Acc	IE00BXNT0820	Robeco QI EM Enhanced Index Equities I $	LU0746585719
Dimensional Emerging Mkts Val A USD	IE00B0HCGS80	Schroder ISF Em Mkts Eq Alp I Acc USD	LU1725196957
DNB Fund Global EM ESG retail A	LU0090738252	Schroder ISF QEP Glbl EM I Acc USD	LU0747139631
DWS Invest Global Emerg Mkts Eqs USD FC	LU0273227354	SLI Global Em Mkts Eq Uncons D Acc USD	LU0778371327
Eastspring Inv Glbl Em Mkts Custmzd Eq E	LU1410579798	State Street Em Mkts Sel Eq P USD	LU1112177008
Eastspring Inv Global EM Dynamic C	LU1558648421	SWC (CH) Equity Fund Emerg Mkts AA USD	CH0004661267
Fisher Invts Instl Em Mkts ESG USD	IE00B65MR018	Swiss Rock Emerg Eq/Aktien Schw E	LU1611484822
GQG Partners Emerging Mkts Eq A USD Acc	IE00BYW5Q130	Swisscanto (LU) EF Sust EM NT USD	LU0866272569
GS EM CORE Eq I Acc USD Close	LU0313358250	Swisscanto Sammelstiftung EM Eq SST2	CH0221964148
GS EM CORE Eq R Acc USD Close	LU0830625504	T. Rowe Price Emerging Mkts Val Eq I USD	LU1244138340
Hector SICAV Eagle Emg Mkts Eq Z USD	LU1104343592	UBAM Global Emerging Equity AC USD	LU0782412331
HSBC GIF GEM Equity Volatility Foc ZC	LU1236621212	UBS (CH) IF Eqs Em Mkts Glbl I-X	CH0018841327
Invesco Emerg Mkt Struct Eq A USD Acc	LU0505655729	UBS (Lux) ES Emerg Mkts Hi Div P USD Acc	LU0625543631
JOHCM Emerging Markets USD B	IE00B4NX0P80	UBS (Lux) ES Emerging Mkts Sust (USD) P	LU0346595837
JOHCM Global Emerging Mkts Opps USD B	IE00B4XXMP29	UBS (Lux) ES Glb EM Opp(USD) U-X USD Acc	LU0399012938
JPM Emerging Markets Div X (acc) USD	LU0862450789	UBS Global Emerging Markets Opp I-B	IE00B3L69P50
JPM Emerging Mkts Divers Eq I (acc) USD	LU0531009297	Vontobel Emerging Markets Eq I USD	LU0278093082
JPM Emerging Mkts Opps X (acc) USD	LU0431994390	Wellington Emerg Mkts Systm Eq S $ AccUh	IE00BYT57D54
JPM Global EM Rsr Enh IdxEq C (acc) USD	LU1468436974	Wells Fargo (Lux) WF EM Eq Inc I USD Acc	LU0791591158

List of emerging market countries, as classified by MSCI

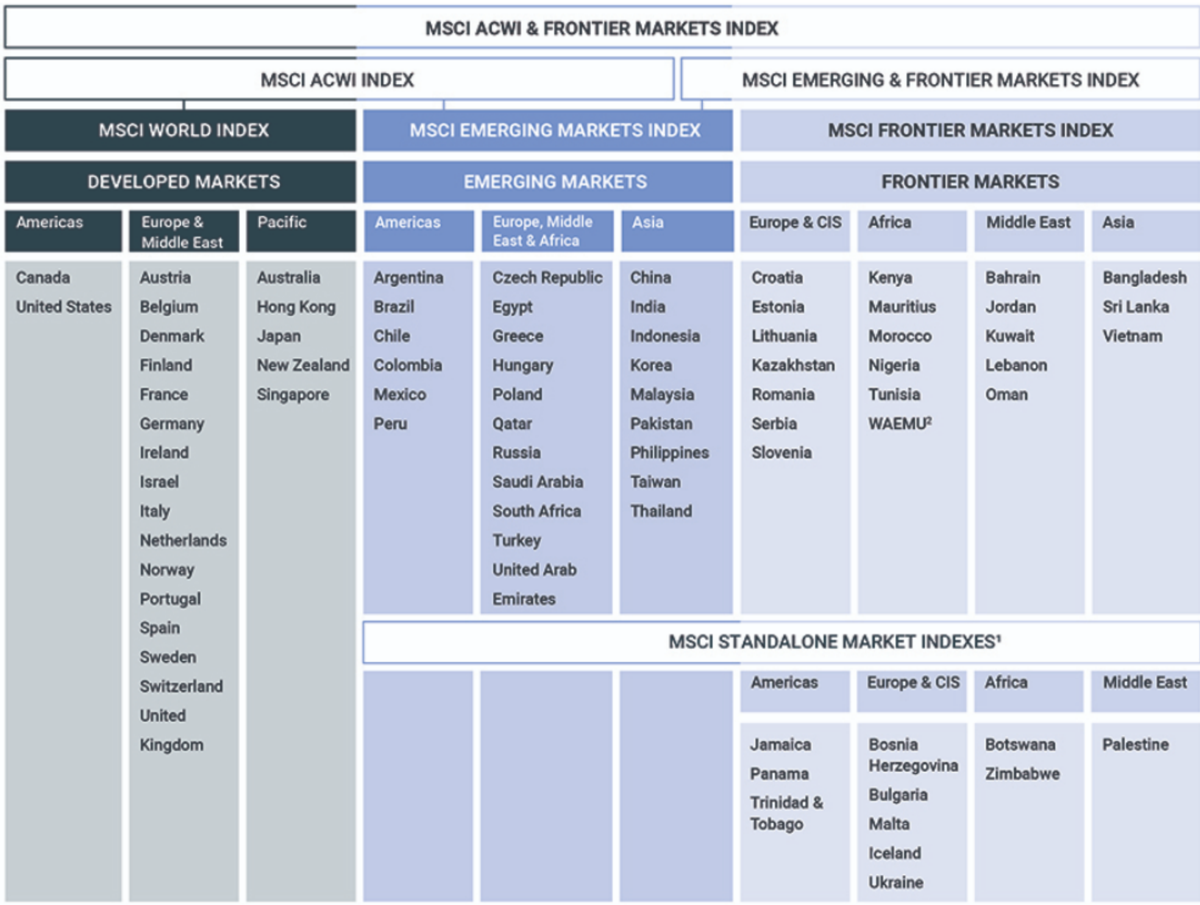

Figure 20: MSCI´s Market Classification *(MSCI, 2019)*

Additional regression models that test for association between mutual fund performance and degree of activity

Table 5 and 7 in section 6.3 depict regression results with the mutual funds' monthly gross returns and 10-year monthly gross Carhart alphas as dependent variables, respectively. In the following, we include net of costs equivalent of this regressions. In addition, we also include results from regressions with CAPM and CAPM Redux alphas as independent variables. As observable, the conclusion remains the same as drawn in section 6.3.

Association between net fund returns and degree of activity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Active share	-0.008*		-0.006	-0.002	-0.081	0.005	-0.012	0.005
	(0.004)		(0.004)	(0.029)	(0.086)	(0.011)	(0.029)	(0.011)
Tracking error		-0.019***	-0.018***	0.058***	-0.185***	0.054***	0.049***	0.048***
		(0.006)	(0.006)	(0.013)	(0.039)	(0.010)	(0.013)	(0.010)
Active share^2				-0.00003	0.001	-0.0001	0.00004	-0.0001
				(0.0002)	(0.001)	(0.0001)	(0.0002)	(0.0001)
Tracking error^2				-0.002***	0.0005	-0.002***	-0.002***	-0.002***
				(0.0004)	(0.001)	(0.0003)	(0.0004)	(0.0003)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Fund fixed effects	Yes	Yes	Yes	Yes	Yes	No	Yes	No
Index	0.937***	0.935***	0.935***	0.936***		0.936***	0.946***	0.946***
	(0.004)	(0.004)	(0.004)	(0.004)		(0.004)	(0.004)	(0.004)
Constant	0.984***	0.720**	1.157***	0.684	12.527***	0.248	0.511	-0.165
	(0.317)	(0.149)	(0.321)	(1.079)	(3.191)	(0.406)	(1.074)	(0.387)
Observations	6,050	6,050	6,050	6,050	6,050	6,050	6,050	6,050
Adjusted R^2	0.903	0.904	0.904	0.905	0.164	0.904	0.904	0.903

Table 13: *Association between net fund returns and degree of activity. Robust standard errors are in parenthesis.*

Association between Carhart net alpha and degree of activity

	(1)	(2)	(3)	(4)
Average active share	-0.002		-0.001	-0.010
	(0.002)		(0.002)	(0.016)
Average active share^2				0.0001
				(0.0001)
Average tracking error		-0.006	-0.005	0.059
		(0.008)	(0.008)	(0.046)
Average tracking error^2				-0.003
				(0.002)
Constant	-0.044	-0.108	-0.033	0.013
	(0.147)	(0.066)	(0.149)	(0.499)
Observations	87	87	87	87
Adjusted R^2	-0.004	-0.004	-0.012	-0.011

Table 14: *Association between Carhart net alpha and degree of activity. Robust standard errors are in parenthesis.*

Association between CAPM gross alpha and degree of activity

	(1)	(2)	(3)	(4)
Average active share	0.0001		0.0004	-0.011
	(0.002)		(0.002)	(0.013)
Average active share^2				0.0001
				(0.0001)
Average tracking error		-0.003	-0.004	0.030
		(0.007)	(0.007)	(0.040)
Average tracking error^2				-0.002
				(0.002)
Constant	-0.073	-0.039	-0.065	0.170
	(0.127)	(0.057)	(0.128)	(0.432)
Observations	87	87	87	87
Adjusted R^2	-0.012	-0.009	-0.020	-0.030

Table 15: *Association between CAPM gross alpha and degree of activity. Robust standard errors are in parenthesis.*

Association between CAPM net alpha and degree of activity

	(1)	(2)	(3)	(4)
Average active share	-0.001		-0.0005	-0.009
	(0.002)		(0.002)	(0.016)
Average active share^2				0.0001
				(0.0001)
Average tracking error		-0.005	-0.005	0.035
		(0.008)	(0.008)	(0.046)
Average tracking error^2				-0.002
				(0.002)
Constant	-0.101	-0.120*	-0.091	0.046
	(0.149)	(0.067)	(0.151)	(0.507)
Observations	87	87	87	87
Adjusted R^2	-0.010	-0.006	-0.018	-0.031

Table 16: *Association between CAPM net alpha and degree of activity. Robust standard errors are in parenthesis.*

Association between CAPM Redux gross alpha and degree of activity

	(1)	(2)	(3)	(4)
Average active share	0.0003		0.001	-0.013
	(0.002)		(0.002)	(0.014)
Average active share^2				0.0001
				(0.0001)
Average tracking error		-0.010	-0.012	0.036
		(0.007)	(0.008)	(0.042)
Average tracking error^2				-0.003
				(0.002)
Constant	-0.211	-0.108*	-0.185	0.088
	(0.138)	(0.061)	(0.138)	(0.462)
Observations	87	87	87	87
Adjusted R^2	-0.011	0.012	0.005	0.003

Table 17: *Association between CAPM Redux gross alpha and degree of activity. Robust standard errors are in parenthesis.*

Association between CAPM Redux net alphas and degree of activity

	(1)	(2)	(3)	(4)
Average active share	-0.001		0.0003	-0.011
	(0.002)		(0.002)	(0.016)
Average active share^2				0.0001
				(0.0001)
Average tracking error		-0.012	-0.013	0.041
		(0.008)	(0.009)	(0.048)
Average tracking error^2				-0.003
				(0.003)
Constant	-0.239	-0.189***	-0.211	-0.036
	(0.157)	(0.070)	(0.157)	(0.528)
Observations	87	87	87	87
Adjusted R^2	-0.011	0.014	0.003	-0.003

Table 18: *Association between CAPM Redux net alphas and degree of activity. Robust standard errors are in parenthesis.*