UNIVERSITY OF GOTHENBURG
SCHOOL OF BUSINESS, ECONOMICS AND LAW

Master Degree Project in Finance

One Instance Not a Trend: Empirical Lack of Persistence in Earnings Prediction

Revisiting the EMH in Sweden with an active fund selection framework

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Abstract

This thesis examines the performance of active fund management in Sweden 2006-2015 by applying a framework to identify mutual fund managers whose index deviations historically have proved successful around earnings announcements. The Active Fundamental Performance (AFP) measure, proposed by Jiang & Zheng (2015), is defined as covariance between deviations from market weights and three-day alpha around earnings. We find no persistence in the measure. The top quintile portfolio exhibit statistically significant negative alphas during the financial crisis and alphas not different from zero afterwards. Our results strengthen the idea of a semi-strong form of market efficiency and have implications for market participants considering whether to invest passively or actively.

Keywords: Active Management, Active Share, Active Fundamental Performance, Efficient Market Hypothesis, EMH, Earnings Prediction, Stock Picking, Fama-French, Sharpe, Jiang & Zheng, Mutual Funds, Sweden

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1 Introduction

This thesis examines the performance of active fund management in Sweden. In regards to asset management, especially when it comes to long-only equities, there are two camps. Those who believe a skilled manager can generate superior returns after accounting for systematic risk exposure and those who believe active management is mostly a waste of resources and investor fees – as long as there remain participants enough to keep markets efficient. Sharpe (1991) wrote the following in an article named The Arithmetic of Active Management: "Properly measured, the average actively managed dollar must underperform the average passively managed dollar, net of costs. Empirical analyses that appear to refute this principle are guilty of improper measurement." … "It is perfectly possible for some active managers to beat their passive brethren, even after costs. Such managers must, of course, manage a minority share of the actively managed dollars within the market in question." We test a hypothesis to identify an outperforming minority by applying an identification framework for mutual fund managers based on their historical success in predicting firm-specific information.

Our study has implications for the debate on market efficiency in Sweden, questioning the value of active management and superior abilities of fund managers to predict earnings, considering our results show negative or no effect on returns from deviating from the market portfolio. With the tools and specifications used in this study to select fund managers, investors would over time earn higher risk-adjusted returns from buying a low cost all-share index fund. We derive this to the Swedish equity market being efficient due to a rather concentrated number of securities and a well-developed financial system. Our suggestions are in line with the strand of research in favor of passive investing. For asset managers and financial advisers this means that emphasis can be more efficiently placed on adapting the market portfolio to investors' individual financial needs rather than focusing on trying to earn abnormal returns. Our robustness tests concerning varying volatility in factor coefficients and the contrasting findings in different time regimes offer additional insight into whether active management is more or less valuable in different market settings. Further, the thesis has constructed a framework offering many additional areas for researchers to investigate, from our structuring of all Swedish fund holdings much data can be aggregated and analyzed. Where we used firm-level data to control for Fama-French's size and book-to-market factors, one could expand the framework additionally. For example manager styles could be investigated on characteristics such as their investments' earnings trends and valuation multiples, investment holding periods etc.

As for the empirical literature, there are results in favor of both strands of thought on the value of active management. Barber & Odean (2000) showed evidence of significant underperformance from active trading. Cremers & Petajisto (2009) and Petajisto (2013) on the other hand showed that funds with the highest measure of Active Share significantly outperform their benchmarks and that the non-index funds with the lowest measure underperform. Cremers & Petajisto define an actively managed fund as starting with the market portfolio and then adding a portfolio of short positions in the stocks you wish to underweight and long positions in the ones you wish to overweight on top of that. Active Share thus represents the sum of those positions, or the share of portfolio holdings that differ from the benchmark. The reasoning behind using Active Share is that it enables capturing both stock selection and factor timing as the two dimensions of beating a benchmark. Grinblatt & Titman (1993) and Lo (2008) used the covariance between weights and subsequent stock performance as an approach to determine whether fund managers are successful at predicting performance.

The question has turned towards how to identify the managers that do manage to outperform, even if it is true that on average the costs and performance fees drag active management below the benchmark returns. If the markets are indeed efficient, any model identifying risk-free profits, i.e. alpha, would quickly be exploited and prices would adjust. As Sharpe (2007) writes; "Methods for beating the market often carry the seeds of their own destruction." Keeping this in mind, this study can thus be considered an examination of market efficiency, rather than just the application of a new model. Our study applies a model in the same spirit as Grinblatt & Titman (1993) and Lo (2008), but uses active portfolio weights, i.e. the deviation from the most resembling benchmark, and a three-day window around earnings announcements to increase the information-to-noise ratio. The ratio of information to noise is expected to be higher close to earnings reports since new information reaches the market and any price change is likely to stem from a revaluation of the firm value rather than random price movements. The framework seeks to combine active management with firm-specific fundamental information. This closely follows the methodology introduced by Jiang & Zheng (2015), but in a different market and time period.

Our method deviates in a numb er of ways: i.) We use only one benchmark index, the OMX Stockholm all-share, for all funds in the sample, whereas Jiang & Zheng use one index out of 19 that minimizes the sum of deviations for each fund. Using an all-share index better reflects the passive alternative of holding the full domestic market portfolio. ii.) We also add an additional restriction that 95 % of fund holdings must exist in the benchmark for the fund to be included in the sample, in order to make sure the managers are indeed considering the benchmark as their investment universe. iii.) We also form size and book-to-market factors based on the OMX Stockholm index for the estimation of the cumulative abnormal returns (CAR) of the index constituents as well as for the risk adjusted abnormal returns in the subsequent portfolio return analysis.

In estimating CAR we consider both CAPM alphas and Fama-French three factor alphas. Since our sample of funds is considerably smaller than Jiang & Zheng's, we form quintile portfolios of funds rather than decile portfolios. As for the results, we find evidence contrary to Jiang & Zheng's as there are no statistically significant positive abnormal returns after constructing fund portfolios based on the

Active Fundamental Performance (AFP) measure. After deriving a plausible source for the deviation from Jiang and Zheng's results to the lack of persistence in the AFP measure for funds over time, we perform robustness tests. We construct two additional portfolio specifications as well as investigate a potential instability in the factor coefficients over time, controlled for by applying a Markov regime switching model during the financial crisis.

There are several reasons why we choose to analyze AFP in Sweden. The Swedish market is relatively concentrated in regards to the number of listed stocks considering the OMX Stockholm all-share index had approximately 305 constituents during our sample period. The ownership structure is also relatively concentrated with a long history of family majority ownership, often utilizing differentiated voting rights. At the same time, it is accessible for foreign investors, Mavruk & Carlsson (2015) points out the strength of the market for corporate control with hostile takeovers from both foreign and domestic firms being common and that the history of highly sophisticated products and technologies, skills and a well-functioning infrastructure has long attracted foreign interest.

Further, there are significant levels of international firms acting as market makers and arbitrageurs in Sweden; Breckenfelder (2013) states that High Frequency Trading (HFT) make up between 50 to 85 % of daily volume when investigating the HFT impact on Nasdaq OMX Stockholm. The level of individual participation in the stock market is high due to a well-developed welfare system with a high share of mandatory savings and a well-established mutual fund industry. All Swedish mutual funds are governed by the Swedish Financial Supervisory Authority (Finansinspektionen, 2016). Their compilation of quarterly mutual fund holdings enables stock-specific analysis of fund manager equity allocation decisions with data continuously updated since 2005.

The main difference from the US sample of 2,455 funds used by Jiang & Zheng (2015) is that the significantly greater number of domestic stocks allows funds to focus on specific sectors or niches while still being sufficiently diversified, whereas in Sweden there are fewer firms to choose from within each sector. [1] Thus there is a trade-off between deviating from the benchmark and diversifying. If the Swedish portfolio is fully diversified and exposed to most sectors, it may end up quite close to the market portfolio. Further, as successful funds grow large, the relatively low liquidity in smaller firms may impede their ability to follow their strategy. The large companies remaining for them to invest in are usually export oriented and will likely be quite recognized and well-covered also by international investors.

[1] According to the World Bank, there were 4,369 listed companies in the US in 2014.

In order to examine active fund performance we use a sample of 67 funds that manage on average 5.002 billion SEK, with an average management fee of 1.24 % from the fourth quarter of 2005 to the third quarter of 2015. The frequency of holdings reporting is quarterly and returns of stocks and funds are measured daily. The starting point of 2005 coincides with the year IFRS reporting standards were enacted in the European Union, which Hamberg, Mavruk & Sjögren (2013) claim significantly increased transparency of financial reporting. This is relevant since our model depend on the market reaction to new earnings-related firm-specific information. The sample time period covers several market sentiments and shifts in perspectives on risk-taking, enabling the contrasting of findings leading up to and after the shock in 2008. Whereas Jiang & Zheng (2015) study the period 1984–2008, our sample starts in 2006 but continues beyond the financial crisis in 2008 up until December 2015, thus reflecting the most recent market conditions. It is not a wild assumption that market efficiency has increased over the last seven years in Sweden due to technological progress and improvements in information distribution. The sample time period also enables contrasting results between regimes switches as the financial crisis may have impacted fund managers' approaches to risk taking. These facts lead us to examine and test whether the Swedish fund market is efficient in the semi-strong version of the EMH in terms of active fund management.

We find that the AFP measure for Swedish mutual funds in the years 2006-2015 exhibit no persistence, in contrast to the findings of Jiang and Zheng (2015). Our results suggest that AFP ranking worsens risk-adjusted returns during the crisis regime between 2006 and 2008. During this regime we obtain statistically significant negative alphas. During the post-crisis regime between 2009 and 2015 we obtain statistically insignificant alphas, thus we cannot conclude whether a strategy based on AFP-ranking generates risk-adjusted returns different from zero. The same holds for the specification based on the Active Share measure. Our results have implications for market participants considering whether to invest in a passive benchmark fund or with an active fund manager, and the results point in the direction of a passive fund, in line with the elementary advice of Sharpe. Considering fund managers' access to information, the findings suggest the Swedish equity market can be considered efficient, an important consideration for any investor.

The rest of the thesis is organized as follows. In Section 2, we present a literature review and develop our hypothesis. In Section 3 we describe our data and outline the methodology. In Section 4 the main regression results are presented and key findings pointed out. In the last section we draw conclusions on the discoveries and discuss their implications.

2 Literature Review & Hypothesis Development

In the same spirit as of our introductory quote by Sharpe, in his book Investors and Markets (2007) he postulates three versions of the Index Fund Proposition, increasing in strength;

- Index Fund Proposition a - Few of us are as smart as all of us.
- Index Fund Proposition b - Few of us are as smart as all of us, and it is hard to identify such people in advance.
- Index Fund Proposition c - Few of us are as smart as all of us, it is hard to identify them in advance, and they may charge more than they are worth.

As for the market capitalizations reflected in index funds, the starting point is that the market portfolio continues to be traded until it is mean variance efficient, as proposed by Markowitz (1952). This implies that no further diversification can lower the risk for a given level of return. Inspired by Galton (1907), Sharpe reaffirms the “Vox Populi” concept (voice of the people, i.e. the wisdom of crowds) as the combined estimates of the group may be accurate enough in pricing assets so that the market portfolio reaches an efficient equilibrium. This holds even if there are several individuals making suboptimal choices in regards to portfolio composition. With this reasoning, the value of fund managers is thus to help satisfy different preferences and outside positions rather than trying to earn abnormal returns.

This relates directly to the efficient market hypothesis with its weak, semi-strong and strong form, as presented and tested by Fama (1970). Especially the semi-strong form is relevant for this thesis considering Fama’s view that monopolistic access to information is the only aspect that might not be fully reflected in prices. Jensen (1969) argues in favor for strong form efficiency since fund managers ought to outperform due their activeness, close contact to the market, high endowment and wide range of contacts, but are nevertheless empirically unable to forecast prices well enough to exceed their research and transaction costs.

An early study by Sharpe (1966) supported the idea of persistence in performance of funds. Persistence can be positive or negative, meaning that good performance is followed by good performance and bad performance is followed by bad performance respectively. Grinblatt et al (1995) found that 77 % of fund managers were momentum investors, buying stocks that were past winners, and that these outperformed their peers. The persistence hypothesis was confirmed but limited to a short time period of one year or less in studies by Carhart (1997) and Chen, Jegadeesh & Wermers (2000). However, Jan and Hung (2004) argued that if persistence exists in the short run it should also exist in the long run, although in a previous paper by Jan & Hung’s (2003), they did not find support for performance persistence.

Grinblatt & Titman (1993) confirmed the existence of both positive and negative persistence. Carhart (1997) only found support for negative persistence. He demonstrated that common factors and investment expenses almost completely explained persistence and claimed the Hendricks, Patel & Zeckhauser (1993) "hot hands" observation is mostly driven by the momentum effect presented by Jegadeesh & Titman (1993). The only persistence not explained was for the strong underperformers. He concludes that the results do not support existence of skilled or informed managers.

Fama (1972) divided fund manager forecasting into micro and macro forecasting, commonly considered as security analysis and market timing respectively. Jensen (1968) found that managers are not able to time the market, Lee & Rahman (1990) found opposing results. In regards to stock picking ability, Grinblatt & Titman (1989, 1993) and Daniel, Grinblatt, Titman & Wermers (1997) found significant evidence of such abilities and that this leads to outperformance. Wermers (2000) later presented contradicting evidence when stating that active funds underperform the passive counterparts and that stock picking ability does not help to generate superior returns.

Despite no lack of prominent research, the topic is still not settled. More recent studies have inspired us to apply an empirical framework for the Swedish mutual fund market. Jiang and Zheng are forming their approach by proceeding from earlier work and methodologies suggested by Grinblatt & Titman (1989, 1993) and extended by Lo (2008). The starting point is the covariance between portfolio weights and subsequent asset returns, and the aggregation of the covariance serves as way to explain manager's ability to forecast asset returns. The AFP methodology deviates from this earlier work in two ways. The measure is based on active fund holdings, which is individual deviations from the most resembling benchmark, rather than just fund holdings without any benchmarking. It also uses the three-day cumulative abnormal return surrounding earnings announcements in order to increase the information-to-noise ratio. Jiang & Zheng (2015) find that funds in the top decile AFP outperform those with low AFP by 2-3% annually during 1984-2008. According to this we state the first hypothesis in the alternative form:

Hypothesis 1: *Portfolios formed by the top quintile AFP funds will produce a higher risk-adjusted return than that of the bottom quintile.*

Jiang and Zheng shows that their measure is persistent for up to six months and for the top decile funds for up to three years, which, even though not guaranteeing superior performance, show that skills of fund managers can be consistent over time. In line with this we formulate the following hypothesis, also in alternative form:

Hypothesis 2: *Fund managers with an AFP in the top quintile in a quarter will continue to have high AFP in the subsequent quarters.*

In addition to this, Lindblom, Mavruk & Sjögren (2015) highlight the effect of the credit crisis in 2008 on the volatility of market returns and suggest a regime switch for the sample. Chen and Huang (2007) present a methodology to capture the effect of different regimes of the volatility of factor returns. Thus we formulate a third hypothesis in the alternative form:

Hypothesis 3: *The factor coefficients for market, size and book-to-market were more volatile during the two years leading up to and including the financial crisis compared to the years after 2008 until late 2015.*

Further, Baker et al. (2010) find evidence that aggregate mutual fund trades forecast earnings surprises and show that some fund managers are skilled in forecasting firm specific fundamentals. Cremers and Petajisto (2009) show that funds with the highest measure of Active Share significantly outperform their benchmarks and that the non-index funds with the lowest measure underperform. The reasoning behind using Active Share is that it enables capturing both stock selection and factor timing as the two dimensions of beating a benchmark. Hence we formulate a fourth hypothesis, also in alternative form:

Hypothesis 4: *Portfolios formed by the top quintile Active Share will produce a higher risk-adjusted return than that of the bottom quintile.*

3 Data and Method

3.1 Data

Our data come from two different sources; the Swedish Financial Supervisory Authority (Finansinspektionen) and Bloomberg. First, we obtain data on fund holdings from the Swedish FSA which is available on a quarterly basis as it is a requirement for the funds in order to comply with FSA rules. Fund holdings data is retrieved starting in Q4 2005 and fund return data to track performance from Q1 2006. The sampling continues until Q3 2015 and Q4 2015 respectively. As of Q3 2015 there were 513 funds reporting, with the data published at most four weeks after the quarter shift. To form a sample of only domestic equity funds, all funds investing in foreign securities and fixed income securities are excluded from the sample. Funds with short-selling mandate are also excluded as we wish to investigate long-only funds. This is because varying mandates such as the ability to leverage and having a net long position of more than 100 % does not reconcile with the reasoning that overweighting some stocks must be matched with equal underweighting in other stocks. Holdings of each fund are listed with ISIN (International Securities Identification Number), which allows us to account for different share classes, based on the stock's assigned voting right, as all share classes are included with different weights in the benchmark index.

Second, we obtain data on prices, earnings announcement dates, market capitalizations and price-to-book ratios for all index constituents from Bloomberg. Across quarters during the sample period the number of index constituents is varying around approximately 305 firms. We also obtain data on mutual funds' NAV (Net Asset Value), management fee, assets under management and inception date from Bloomberg. Historical data on liquidated firms and funds is still available so we could include all funds in the FSA database that have existed but disappeared due to different reasons during the sample period, thus preventing survivorship bias. By dealing with the survivorship bias problem, we avoid the risk of overestimating the historical performance of Swedish mutual funds as liquidated funds' contribution to the overall performance is taken into consideration and not only the funds that survived.

The sample consists of 67 all-equity Swedish funds. In Table 1 descriptive statistics on these are shown in Panel B. The funds manage on average 5.002 billion SEK, with an average management fee of 1.24 % and have an average age of 15.5 years. Arithmetic returns of stocks and funds are measured daily. The average annualized return during the sample was 9.29 % with a standard deviation of 21.84 %. The fund selection criteria before entering an AFP portfolio require that at least 95 % of total holdings in the fund must be publicly listed and included in the OMX Stockholm All Share Index.

Table 1, Panel A, contains the input variables used for calculating the two components of the AFP measure; active holdings and cumulative abnormal returns (CARs). Active holdings are formed by fund weights and index weights. CARs are formed by three-day returns, Fama-French three factor coefficients and the corresponding factor returns. To calculate these factors we divided all benchmark constituents into 2x3 size and book-to-market portfolios following the methodology by Fama & French (1992). The average holding weight in the average fund in the average quarter is 2.43 % with a standard deviation of 1.05 %. The smallest holding is on average 0.31 % over quarters. The largest over quarters was on average 8.09 %. As for the index, the cross-sectional average weight was 0.35 % with a significantly smaller minimum weight on average compared to the funds, at 0.0001 %. The average largest over time of 10.82 % is quite similar to that of the funds. The average number of holdings in a fund was 53.3 with a maximum in a quarter of 147 and a minimum of 15. When looking at the fit between fund holdings and the index benchmark as the investment universe, the average share of holdings outside the index, e.g. share subscription rights, options, an instance of a foreign holding, a treasury or a privately listed share, was 4.47 %. The standard deviation of 5.73 % in this measure gives an indication of how often funds were excluded from the AFP ranking. The cumulative three-day return around earnings was on average 0.0154 % with a standard deviation of 1.05 %. The coefficients for market, size and book-to-market averaged 0.9215, 0.6469 and 0.0156 respectively over the sample period. The average three-day factor returns are also shown. Descriptive statistics on the combined output of these variables into CAR and AFP is presented in the analysis section.

Table 1: Descriptive Statistics Input Variables

Panel A: Input Variables	
Weights across quarters and funds[2]	
Cross-sectional average	2.43 %
Cross-sectional std. dev.	1.05%
Average minimum for a quarter	0.31%
Cross-sectional minimum	9.6E-09 %
Average maximum for a quarter	8.09%
Cross-sectional maximum	20.23%
Index Weights	
Cross-sectional average	0.35%
Cross-sectional std. dev.	1.12%
Average minimum for a quarter	0.0002%
Cross-sectional minimum	0.0001%
Average maximum for a quarter	10.82%
Cross-sectional maximum	17.15%

[2] Only includes those holdings existing in the market benchmark

Three-day cumulative return around earnings	
Cross-sectional average[3]	0.0154 %
Standard deviation	1.05 %
Average FF3 factor coefficients estimation period 120 days prior to earnings	
Market	0.9215
SMB	0.6469
HML	0.0156
Average FF3 factor three-day cumulative return around earnings	
Market[2]	0.45 %
SMB	0.20 %
HML	0.24 %

Panel B: Funds

Fund Characteristics			
as of Sep 30th 2015	**MGMT Fee, %**	**AUM, mSEK[4]**	**Age, years**
Average	1.24	5002.97	15.53
Minimum	0.15	6.22	0.05
Maximum	1.75	30967.00	42.77
10th pct.	0.41	165.12	4.15
25th pct.	1.18	650.96	9.87
Median	1.40	2545.68	15.55
75th pct.	1.50	6007.94	20.29
90th pct.	1.60	13973.66	26.08

Fund Returns			
Nr. Obs.	126 040	**Distribution**	
Mean Return	0.04%	99th pct	3.90%
Std. Deviation	1.38%	90th pct	1.42%
Ann. Return	9.29%	75th pct	0.72%
Ann. Std Dev.	21.84%	Median	0.11%
		25th pct	-0.60%
Nr. obs > |10 %|	22	10th pct	-1.46%
Nr. obs > |5 %|	1 295	1st pct	-4.13%
Nr. obs > |2.5 %|	8 008		

Number of holdings in funds	
Cross-sectional average (over funds & quarters)	53.3
Cross-sectional standard deviation	26.3
Cross-sectional max	147
Cross-sectional min	15
Cross-sectional average mismatch	-4.47 %
Cross-sectional standard deviation of mismatch	5.73 %

3 If all stocks reported on the same day, the average return for stocks and the market return would have been the same.

4 Asset Under Management (AUM)

3.2 Methodology

For each fund in each quarter we calculate the Active Fundamental Performance as the sum of the covariance between the active share and the individual stock's Cumulative Abnormal Return around its earnings announcement. In order to assess the measurement's predicting power for mutual fund returns we form portfolios based on each fund's AFP to compare the top and bottom quintile. A high, positive AFP is the result from overweighting gaining stocks and underweighting losing stocks while a negative AFP is the result from the opposite.

Equation 1 - AFP

$$AFP_{j,t} = \sum_{i=1}^{N_j} \left(w_{i,t}^{j} - w_{i,t}^{b}\right) * CAR_{i,t}$$

Where $AFP_{j,t}$ is mutual fund j's active fundamental performance in quarter *t*, $w_{i,t}^{j}$ is the weight of stock *i* in fund *j's* portfolio in quarter *t*. $w_{i,t}^{b}$ is the weight of stock *i* in the benchmark portfolio in quarter *t*. $CAR_{i,t}$ is stock *i's* three-day cumulative abnormal return around the earnings announcement in quarter *t*. N_j is the number of stocks in fund *j's* benchmark index (Jiang & Zheng, 2015). The equation works as the cornerstone of the framework. Each component of the specification is individually examined and described below.

3.2.1 Active Holdings

The starting point is in active holdings, i.e. the deviation from the benchmark for each stock. The market weight for each index member is deducted from each fund's weight in the corresponding stock and this is done for all stocks in the all-share index. The expected value of active holdings for each fund should by construction be equal to zero. The reason is that if the fund manager decides to overweight some stock, she must underweight in others as described in Jiang and Zheng (2015) and Cremers and Petajisto (2009). Based on this reasoning, a lack of a position in one of the index constituents is considered as underweighting that stock by the magnitude of the index weight. The benchmark is considered to be the investment universe and a differing weight implies manager expectations that deviate from the market. See the simplified example below, imagining there were only five stocks available to invest in.

Table 2: Active Holdings Exemplified

Constituents	**Index weight**	**Fund weights**	**Active Holdings**
ABB	20%	35%	15%
Ericsson	25%	0%	-25%
Holmen	10%	30%	20%
Securitas	15%	5%	-10%
Volvo	30%	30%	0%
Sum	**100%**	**100%**	**0%**

Exemplified in the table above, the index weight and the fund weight of ABB is 20 % and 35 % respectively. Relative to the benchmark index, the fund is overweighting ABB by 15 percentage points, which is contributing to the funds active holdings. Taking each stock's weight in the benchmark index and contrasting this to the stock's weight in the fund yields the active holdings of the fund, which by construction adds up to zero. See Table 7 in section 4 for descriptive statistics regarding active holdings.

3.2.2 Cumulative Abnormal Return (CAR)

CAR is defined as the three-day abnormal return around earnings after accounting for the risk of the market, of size and of book-to-market. To compute CAR as well as abnormal fund portfolio returns we calculate these factor returns. Each quarter we divide all benchmark members into 2x3 size and book-to-market portfolios following the methodology by Fama & French (1992). The respective portfolios are value weighted with daily arithmetic returns[5]. The factor returns for size and book-to-market are retrieved from the following two formulas. *Big* and *small* refers to companies above and below the median market capitalization while *value*, *mid* and *growth* refers to belonging to the first, second or third tertile with respect to book-to-market ratio.

Equation 2 - SMB Factor

$$R^{smb} = \frac{1}{3} * (small\ value + small\ mid + small\ growth) - \frac{1}{3} * (big\ value + big\ mid + big\ growth)$$

Equation 3 - HML Factor

$$R^{hml} = \frac{1}{2} * (small\ value + big\ value) - \frac{1}{2} * (small\ growth + big\ growth)$$

We estimate the coefficients for each of the three factors by regressing all stocks' daily arithmetic returns 120 days prior to earnings. These coefficients are then inserted in the following calculation when estimating the three-day earnings announcement CAR for each stock *i*.

[5] We are calculating the arithmetic returns rather than geometric returns. This is because CAPM requires arithmetic returns for summation in the OLS, there is no compounding effect in the stock market and using geometric returns would generate the power CAPM beta rather than standard CAPM beta as suggested by Sharpe (2007).

Equation 4 - Cumulative Abnormal Return (CAR)

$$\sum_{t=1}^{T} R_t^i - \beta_i * R_t^{mkt} - \gamma_i * R_t^{smb} - \delta_i * R_t^{hml}$$

3.2.3 Active Fundamental Performance (AFP)

The final step to compute AFP is to estimate the covariance between active share and CAR. Due to the expected value of all active holdings being zero, the second expression on the right hand side in the equation below disappears.

Equation 5 - Covariance Active Weights and CAR

$$\begin{aligned} Cov\left(w_{i,t} - w_{i,t}^b, CAR_{i,t}\right) &= E\left[\left(w_{i,t} - w_{i,t'}^b\right) * CAR_{i,t}\right] - E\left(w_{i,t} - w_{i,t}^b\right) * E\left(CAR_{i,t}\right) \\ &= E\left[\left(w_{i,t} - w_{i,t'}^b\right) * CAR_{i,t}\right] - 0 * E\left(CAR_{i,t}\right) \\ &= E\left[\left(w_{i,t} - w_{i,t'}^b\right) * CAR_{i,t}\right] \end{aligned}$$

This simplifies AFP to the sum of the product of active holdings and CAR as seen below along with a simplified example. The active share of the ABB stock in the Fund is 15 %. The product of the active holdings of 15 % times the three-day CAR for ABB equals 2.25 %. Repeating this for all the index constituents the sum of the products of the fund's active shares and their three-day CAR constitutes the AFP for the Fund in quarter *t*, in this case 0.15%.

Equation 6 - AFP

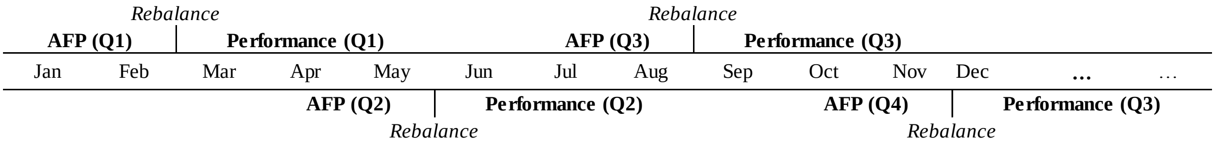
$$AFP_{j,t} \sum_{i=1}^{N_j} \left(w_{i,t}^j - w_{i,t}^b\right) * CAR_{i,t}$$

Table 3: AFP Exemplified

Constituents	Active Holdings	CAR	Active Holding * CAR
ABB	15%	15%	2.25 %
Ericsson	-25%	10%	-2.5 %
Holmen	20%	-2%	-0.4 %
Securitas	-10%	-8%	0.8 %
Volvo	0%	3%	0%
AFP			**0.15 %**

Jiang & Zheng (2015) showed that AFP stabilizes two months following the turn of a quarter and that companies reporting earnings more than two months afterwards do not impact the measure significantly. The same observation was made for our data set, where AFP appears to stabilize after 9 weeks. In a conservative manner, to account for slower reporting in some quarters and to be able to compare our results to Jiang & Zhang, we set 10 weeks as the measuring point (Figure A-2, Descriptive Statistics Appendix). After this quarterly measurement, the quintile portfolios of funds are rebalanced until the next quarter's measurement date, see timeline below.

Figure 1: AFP Timeline



The final step after going through the framework each quarter is to sort the funds by their AFP measure and to use this as ranking in order to compare the performance of the funds with the highest AFP to those with the lowest. We do this by forming quintile (five equally sized) portfolios where quintile 5 includes the top AFP and quintile 1 the bottom. The funds in each quintile are weighted equally in line with Jiang and Zheng (2015) and the fund's daily arithmetic returns on NAV are regressed on Fama & French's three factors as described previously as well as by using the CAPM model by Sharpe (1964).

3.2.4 Positive and Negative AFP

The observed absence of persistence in funds' AFP measure led us to generate alterative specifications in order to further test the results retrieved for the AFP specification. We call these portfolios positive and negative AFP, the former with strictly positive AFP funds and the latter with strictly negative ones. When examining the characteristics of the AFP measure it becomes evident that it is not necessarily the case that just because quintile 1 contains the lowest, often negative AFP funds and that quintile 5 the highest, that the funds in quintile 3 are the ones who have deviated the least from the market. The fact is that the breaking point for AFP equal to zero wanders around quite heavily among the quintiles, which is depicted in figure 2 below that shows which quintile portfolio the fund with closest to zero AFP score is located in. In some quarters there were no or very few funds with deviating sign on AFP, and rather than to compare a zero return or an insufficiently diversified portfolio, in those quarters the three lowest of the positive or the three highest of the negative form a portfolio. Figure 3 graphs the share of funds with a positive AFP score over the 39 quarters measured and illustrates how volatile the swings in AFP scores are between quarters and that funds often fall on the same side of the zero AFP mark.

Figure 2: Illustration of Breaking Point for positive AFP

The figure shows the number of times that the breaking point between negative and positive AFP scores ended up in each of the quintile portfolios. It aims to illustrate that it cannot be assumed that the least deviating fund is found in the mid-quintile.

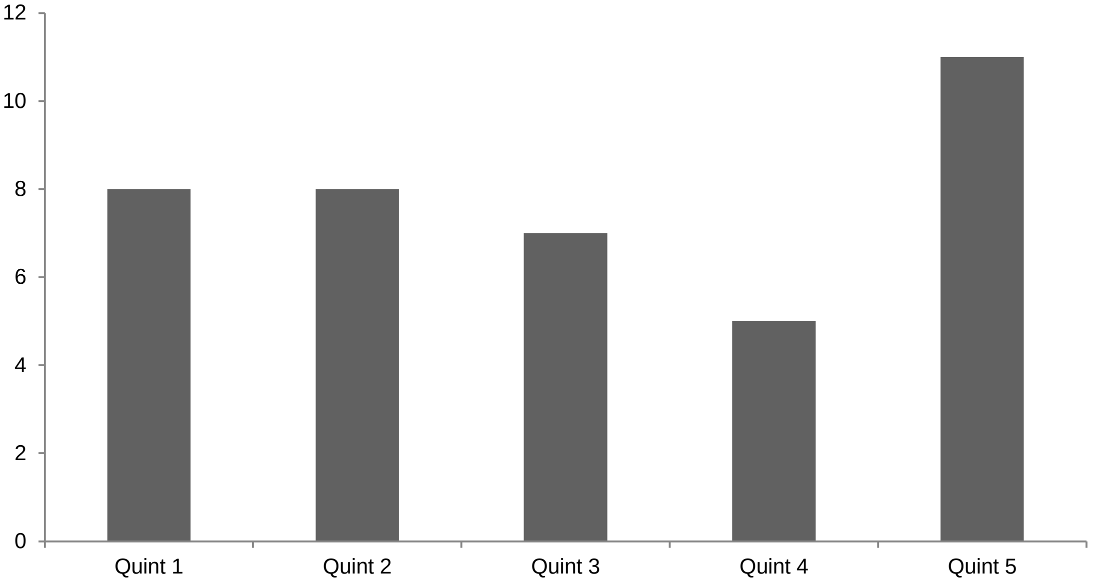
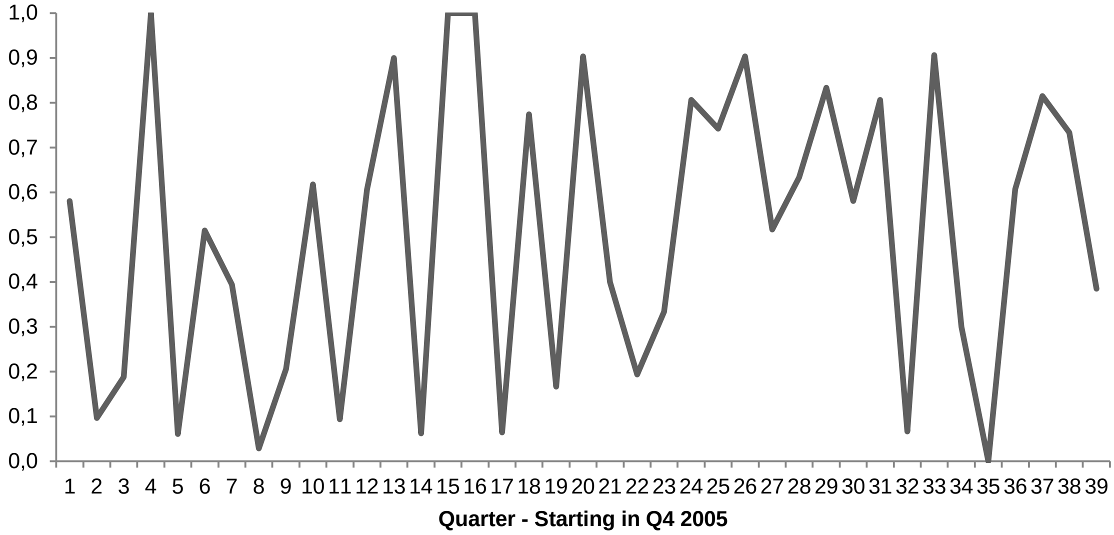


Figure 3: AFP Characteristics

The figure shows the percentage share of funds in the sample that have a positive AFP score over the quarters. It aims to illustrate that funds often share the same outcome in regards to benefitting or harming from their active holdings.

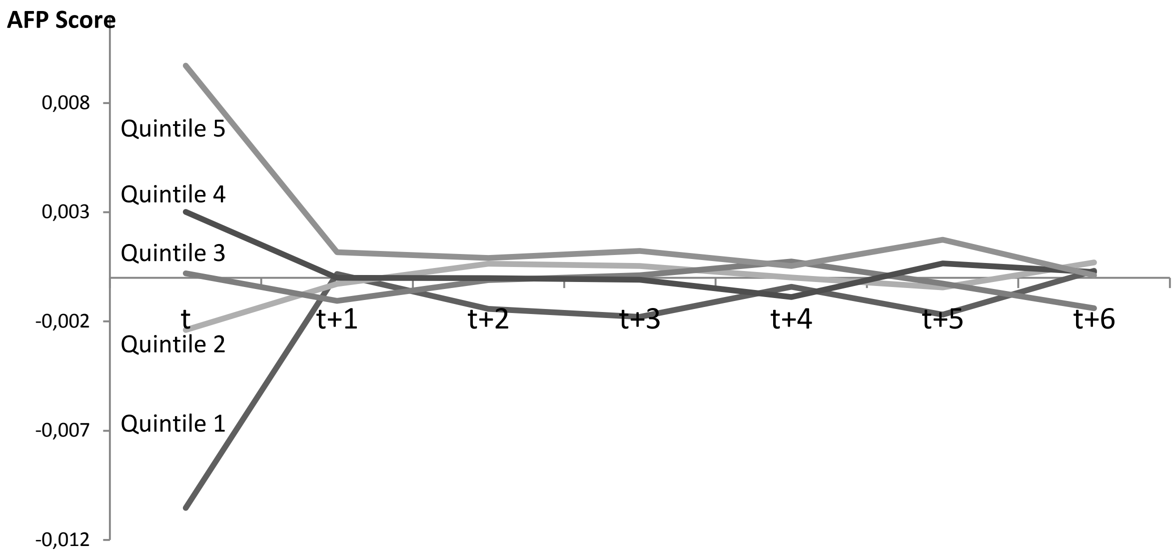


3.2.5 Persistence in AFP

Depicted below is the average AFP measure of the quintile portfolios for the current and the 6 subsequent quarters, averaged over our full sample period. The AFP measure for each quintile is represented in relative terms, so that it is the difference from the full sample average shown in the graph. Even though quintile 5 remains with the highest AFP in some quarters, it is with a low margin, and notably, quintile 1 is not persistently among the worst.[6]

Figure 4: Persistence in AFP

The figure shows the average AFP score in the six subsequent quarters after portfolio formation and is averaged over the full sample period. It aims to illustrate that there is no persistence in the AFP measure and is used as a motivation for further specifications.



Due to this apparent lack of persistence in AFP differences, we define an additional portfolio composition. Although Jiang & Zheng show persistence in AFP for up to 6 quarters and even longer for the top decile, our sample does not yield similar results. Therefore we set another restriction on the quintile formation and create two more portfolios. For the two “persistent AFP” portfolios the first criterion is to qualify for quintile 1 or 5 respectively, and based on these candidates, only the ones with the highest historical persistence of being in that quintile during the last year are included. We set the restriction that at least five funds are included in order to guarantee a sufficient diversification.

[6] For the same type of persistence graph, but with opposite results, see Figure A-1 in Descriptive Statistics Appendix graph based on quintiles from active holdings.

3.2.6 Active Share

As active management overall being successful is a prerequisite for AFP to act as a more detailed specification, examining the statistical relationship between active management and risk-adjusted performance becomes central. As an extension of our AFP specification we follow Cremers & Petajisto (2009) by calculating Active Share, ranking and forming quintile fund portfolios. The measure represents the share of portfolio holdings that are different from the market index and is calculated using the following formula.

Equation 7 - Active Share

$$\text{Active Share } = \frac{1}{2} * \sum |w_i - w_b|$$

Our Active Share measure is based on the Swedish FSA data on the quarter shift, the portfolios are formed the following business day and held until the subsequent quarter. The timeline of such a strategy is not applicable in reality for a mutual fund investor, as the FSA data is not released until approximately 25 days after the quarter shift. In our AFP specification, this is not an issue as time passes until earnings announcements and the portfolio is formed, but here the specification will act as theoretical research rather than a possible investing strategy. It does provide backtesting for our sample period to study the differences in performance between active and inactive managers and serves to assist our analysis of the AFP results.

3.2.7 Regression Model

To evaluate the predicting power of abnormal returns we use a portfolio analysis framework by estimating time series regression models. The funds are sorted into quintile portfolios that are rebalanced quarterly and the arithmetic returns are based on daily closing prices.

We estimate the risk-adjusted abnormal return from the following times series regressions.

Equation 8 - CAPM Time Series Regression

$$R_{p,t} - R_{f,t} \ = \ \alpha_p + \beta_m\left(R_{m,t} - R_{f,t}\right) + \ \varepsilon_{p,t}$$

Equation 9 - Fama & French Three-Factor Times Series Regression

$$R_{p,t} - R_{f,t} \ = \ \alpha_p + \beta_m\left(R_{m,t} - R_{f,t}\right) \ + \ \beta_{smb} SMB_t + \beta_{hml} HML_t \ + \ \varepsilon_{p,t}$$

Where $\mathrm{R_{p,t}}$ is the return for portfolio p in day t, $\mathrm{R_{f,t}}$ is the daily rate for a one-month Swedish STIBOR note in day t, $\mathrm{R_{m,t}}$ is the value weighted-return for the SAX index in day t, SMB_t is the difference in returns for small and large cap stocks in day t and HML_t is the difference in returns between high and low book-to-market stocks in day t.

3.2.8 Robustness Tests

We consider the possibility of the coefficients of the factor returns in the estimated regressions to be more or less volatile during different market conditions, which can be explained by higher risk premiums required by investors when markets are in distress. The time-variant factor coefficients in turn affect the abnormal risk adjusted returns and cause them to vary depending on market climate. Empirical results point out that the factor coefficients may be time-varying and in particular Huang (2007) concluded that the factor coefficients can stem from different regimes in the time-variant time series regression model. As Lindblom, Mavruk & Sjögren (2015) state, the financial crisis in 2008 had a large impact on the volatility on market returns and therefore the authors suggest a regime switch for the sample. To deal with this we follow the methodology by Chen and Huang (2007), which in turn is based on the Markov switching model of Hamilton (1994). The Markov switching model is a frequently used nonlinear time series model that is able to capture, in comparison to a linear OLS setup, more complex dynamics between different structures of financial and economic variables over time (Kuan, 2002).

We control for the endogenous regime switching by using the Movestay package in Stata (2016). The Movestay command provides a maximum likelihood estimation of endogenous switching regression or Markov switching models and it deals with the potential presence of nonlinearities in returns in our sample caused by the financial crisis. This full information maximum likelihood method fits the binary and continuous aspects and provides consistent standard errors (Lokshin & Sajaia, 2004).

Another approach to capture the effect of different volatility regimes associated with the financial crisis is that we include a trend variable in the regression estimation. The reasoning behind the inclusion of a trend is to capture the cumulative effect of the economic shock associated with the financial crisis in 2008. The trend variable is assigned the value of 1 for the first quarter in 2006 and ranges to 39 for the fourth quarter in 2015.

We control for potential correlation between returns that does not affect observations individually but uniformly within each group. We allow for correlation between portfolio returns within quarters and assume independence between portfolio returns across quarters. By clustering observations within quarters we ensure a robust standard error structure (Lokshin & Sajaia, 2004).

4 Analysis

In this section we present our main results and analysis for the AFP and the Active Share specification.

Table 4 provides descriptive statistics in order to strengthen the understanding of our data set and the input variables included. Tables 5-6 are regression outputs for the AFP specification. In section 4.1.1 we are motivating the usage of a Markov switching model caused by parameter instability by analyzing the behavior of these parameters during different time periods. We repeat the same procedure for the Active Share specification in Table 10-12.

The AFP specification provides results in the CAPM and FF3 framework that makes us unable to reject the null hypothesis of Hypothesis 1, meaning we cannot confirm the hypothesis of high AFP fund outperformance. We retrieve no significant results suggesting that portfolios formed on the basis of their AFP generate superior returns. This is in contrast to the results presented by Jiang and Zheng (2015), and in addition to failing to support Hypothesis 1; we also cannot reject the null of Hypothesis 2. The null hypothesis that fund managers show no persistence cannot be rejected and thus we cannot confirm the alternative form that there is positive persistence. Hypothesis 1 and 2 are intertwined since the absence of superior performance of top quintile funds relative to bottom quintile funds may well be derived to the lack of persistence in the AFP measure itself. If a fund manager is to be chosen based on her past ability to predict earnings, then this ability better be sustainable for her to be a good long-term choice.

The results in Table 7 with descriptive statistics on factor returns enable us to reject the null hypothesis of Hypothesis 3 which supports the research question of whether factor returns were more volatile in the years leading up to and including the financial crisis compared to the years after. This is in line with the findings of Lindblom, Mavruk and Sjögren (2015). This result causes us to extend our analysis and control for endogenous regime switching caused by this difference in volatility between regimes as is done in Table 8 and Table 9 for the AFP specification and in Table 12 for the Active Share specification respectively.

We extend the analysis by ranking the portfolios based on the Active Share as suggested by Cremers and Petajisto (2009). In contrast to their findings we cannot reject the null of Hypothesis 4 since the active share specification generates results in line with the AFP specification, meaning that the top active share quintile does not produce a higher risk-adjusted return compared to the bottom active share quintile. This becomes evident in the CAPM, FF3 and Markov regime switch model output in Table 10-12.

Table 4: Descriptive Statistics AFP

The table presents descriptive statistics of the two input components producing the AFP measure for a fund, as well as descriptive statistics for the AFP in Panel C. In Panel A the active holdings is presented and in Panel B the cumulative abnormal returns for the corresponding holdings. The estimated CAR is the cumulative three-day alpha from a Fama & French three-factor regression model

Panel A: Active Holdings	
Cross-sectional average	0,00%
Cross-sectional std dev	0.0071%
Average largest overweight	5,10%
Average largest underweight	-9,70%
Cross-sectional largest overweight	20.20%
Cross-sectional largest underweight	-17,20%

Panel B: CAR from FF3 Alphas			
Total nr of observations	9 852		
Cross-sectional Mean	-0.57%	**Distribution**	
Cross-sectional Std Dev	7.93%	99th pct	20.28%
		90th pct	7.94%
Cross-sectional Max	143.38%	75th pct	3.22%
Cross-sectional Min	-86.50%	Median	-0.46%
		25th pct	-4.37%
Nr. obs within 1 std dev	7 672	10th pct	-8.93%
(-7.93 % to 7.92 %)	77.9%	1st pct	-21,83%
Nr. obs within 2 std dev	9 386		
(-15.85 % to 15.84 %)	95.3%		

Panel C: AFP from FF3 alphas			
Nr. obs	1 423		
Avg. funds over time	36.5		
		Distribution	
Cross-Sectional Mean	0.0006	99th pct	0.0338
Cross-Sectional Std Dev	0.0119	90th pct	0.0160
		75th pct	0.0070
Cross-Sectional Max	0.0498	Median	0.0003
Cross-Sectional Min	-0.0638	25th pct	-0.0076
		10th pct	-0.0127
Nr. obs within 1 std dev	1 016	1st pct	-0.0249
(-0.0112 to 0.01250)	71.4%		
Nr. obs within 2 std dev	1358		
(-0.0231 to 0.02437)	95.4%		

In Table 4 Panel A, the average active weight for a typical fund in the average quarter was -0.00089 %. By construction, this measure ends up close to zero since all overweights must be made up for by a corresponding underweight. The small difference is due to the mismatch for when funds invest small amounts outside of the all-share index. Since it is the quintiles of the two opposite endpoints in AFP that is of primary interest, the smallest and largest deviations from index have a large impact. The average of the largest overweight over quarters was 5.07 %, with a standard deviation of 1.76 % and a cross-period maximum of 20.20 %. The average of the largest underweight was -9.7 % with a standard deviation of 2.73 % and a cross-period maximum of -17.15 %.

After deducting the factor coefficient times the factor returns from each three-day return, as described in the method section, the CARs in Panel B above were obtained. The average abnormal return in this FF3 alpha specification was -0.57 % with a standard deviation of 7.93 %. 77.9 % of all observations lie within one standard deviation and 95.3 % lie within two. There are a few outliers as seen from the cross-sectional maximum and minimum, however, judging from the distribution of the input variables the number of extremes is limited.

Combining the two input variables above creates an AFP measure for each fund in each quarter, descriptive statistics on this is presented in Panel C. The average AFP is 0.0006 with a standard deviation of 0.0119. 71.4 % of observations fall within one standard deviation and 95.4 % fall within two. The maximum cross-sectional AFP is 0.0498 and the minimum -0.0638. The figures on AFP can be interpreted as the additional abnormal return that was generated during the three days around earnings due to deviating from the market.

4.1 AFP Framework

Table 5: CAPM AFP

In Table 5 we form quintile portfolios based on funds' AFP score and estimate the CAPM time series regression model. The quintile portfolios are formed and rebalanced 10 weeks after each quarter from the first quarter in 2006 to the fourth quarter in 2015. Quintile 5 is the portfolio consisting of funds with the highest AFP score. In panel A we regress each portfolio return on the market factor for the entire time period, panel B for the time period 2006-2008 and panel C for the time period 2009-2015. We allow for partial correlation between returns and the standard errors are clustered within quarters[7]. Standard errors are presented in parenthesis and ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A : 2006-2015

VARIABLES	q5	q4	q3	q2	q1	topminusbottom
mkt	0.8049***	0.8376***	0.8701***	0.8237***	0.8139***	-0.0089
	(0.0091)	(0.0092)	(0.0088)	(0.0090)	(0.0090)	(0.0060)
Constant	0.0001	0.0001	0.0001	0.0001	0.0002	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	2,374	2,374	2,374	2,374	2,374	2,374
R-squared	0.7663	0.7780	0.8049	0.7792	0.7765	0.0009

Panel B: 2006-2008

VARIABLES	q5	q4	q3	q2	q1	topminusbottom
mkt	0.7977***	0.8501***	0.8977***	0.8359***	0.8323***	-0.0346***
	(0.0166)	(0.0161)	(0.0152)	(0.0165)	(0.0151)	(0.0114)
Constant	-0.0003	-0.0001	0.0000	-0.0001	0.0000	-0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)
Observations	685	685	685	685	685	685
R-squared	0.7722	0.8032	0.8369	0.7895	0.8174	0.0133

Panel C: 2009-2015

VARIABLES	q5	q4	q3	q2	q1	topminusbottom
mkt	0.8095***	0.8271***	0.8481***	0.8134***	0.7989***	0.0107
	(0.0110)	(0.0114)	(0.0110)	(0.0108)	(0.0114)	(0.0070)
Constant	0.0002	0.0002	0.0002	0.0002	0.0002*	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	1,689	1,689	1,689	1,689	1,689	1,689
R-squared	0.7615	0.7578	0.7794	0.7705	0.7448	0.0014

In Table 5 no statistically significant risk adjusted returns for any quintile were obtained, no significant difference between the top and bottom quintile and no factor coefficients provided any significant insight. This also holds when dividing the sample period into two with 2009 as the breaking point, which stands in contrast to Jiang and Zheng's results. Across all quintiles and for all 3 specifications the coefficients on the market return are ranging from 0.79 to 0.89 and the R-squared coefficient is ranging from 0.75 to 0.80.

[7] Stata does not provide an F-statistic after a clustered regression due to the usage of Huber variances (www.stata.com/statalist). In the Regression Output Appendix unclustured regressions with F-Statistic are presented for both the AFP and the Active Share framework.

Table 6: FF3 AFP

In Table 6 we form quintile portfolios based on funds' AFP score and estimate the Fama & French three-factor time series regression model. The quintile portfolios are formed and rebalanced 10 weeks after each quarter from the first quarter in 2006 to the fourth quarter in 2015. Quintile 5 is the portfolio consisting of funds with the highest AFP score. In panel A we regress each portfolio return on the market factor for the entire time period, panel B for the time period 2006-2008 and panel C for the time period 2009-2015. We allow for partial correlation between returns and the standard errors are clustered within quarters. Standard errors are presented in brackets and ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A : 2006-2015

VARIABLES	q5	q4	q3	q2	q1	topminusbottom
mkt	0.9680***	0.9681***	0.9684***	0.9174***	0.9515***	0.0165
	(0.0184)	(0.0086)	(0.0108)	(0.0162)	(0.0098)	(0.0097)
smb	0.3716***	0.2965***	0.2301**	0.2186***	0.3130***	0.0586
	(0.0385)	(0.0298)	(0.0452)	(0.0117)	(0.0436)	(0.0407)
hml	0.0124	0.0066	0.0321	0.0272	0.0076	0.0048
	(0.0352)	(0.0389)	(0.0316)	(0.0352)	(0.0314)	(0.0226)
Constant	-0.0001	-0.0001	-0.0000	0.0000	0.0000	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	2,374	2,374	2,374	2,374	2,374	2,374
R-squared	0.7965	0.7960	0.8155	0.7895	0.7977	0.0084

Panel B: 2006-2008

VARIABLES	q5	q4	q3	q2	q1	topminusbottom
mkt	1.0108***	0.9878***	0.9997***	0.9595***	0.9500***	0.0609*
	(0.0239)	(0.0070)	(0.0241)	(0.0141)	(0.0131)	(0.0231)
smb	0.4745***	0.3045***	0.2219**	0.2702***	0.2612**	0.2133*
	(0.0576)	(0.0336)	(0.0627)	(0.0125)	(0.0500)	(0.0758)
hml	-0.1882*	-0.1459*	-0.1522**	-0.1701*	-0.1121	-0.0761
	(0.0684)	(0.0528)	(0.0443)	(0.0674)	(0.0521)	(0.0627)
Constant	-0.0002	-0.0000	0.0000	-0.0000	0.0001	-0.0003
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	685	685	685	685	685	685
R-squared	0.8187	0.8212	0.8467	0.8049	0.8312	0.0986

Panel C: 2009-2015

VARIABLES	q5	q4	q3	q2	q1	topminusbottom
mkt	0.9432***	0.9551***	0.9448***	0.8887***	0.9522***	-0.0090
	(0.0153)	(0.0181)	(0.0134)	(0.0278)	(0.0183)	(0.0044)
smb	0.3233***	0.3090***	0.2578***	0.2050***	0.3648***	-0.0414
	(0.0238)	(0.0354)	(0.0347)	(0.0191)	(0.0392)	(0.0277)
hml	0.0717***	0.0678	0.1150***	0.1009**	0.0662	0.0055
	(0.0215)	(0.0439)	(0.0188)	(0.0266)	(0.0285)	(0.0224)
Constant	-0.0001	-0.0001	-0.0001	0.0000	-0.0001	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	1,689	1,689	1,689	1,689	1,689	1,689
R-squared	0.7856	0.7788	0.7957	0.7820	0.7752	0.0056

In Table 6 we regress each portfolio return on the Fama-French three factor framework. The R-squared coefficient ranges from 0.77 to 0.84 for the different specifications and no significant alphas were obtained for the entire period as well as when breaking the time period into two and again the results stand in contrast Jiang and Zheng's.

The coefficients on factor returns; market and size provides statistically significant results in line with our expectations with a greater economic significance for the coefficient on the market factor in the first time period and with some variation for the size factor between the Panel B and Panel C.

The market coefficient is close to 1 for all portfolios in Panel A, Panel B and Panel C with the exception of quintile 2 in the bottom panel. The greater economic significance in this three-factor specification compared to the CAPM specification in Table 4 is due to when we control for the size and value effect, we isolate the market risk exposure of the portfolios consisting of well diversified funds which approach the market portfolio, i.e. a coefficient of 1.

The book-to-market factor show no significant results in the first setup which is in line with Lindblom, Mavruk & Sjögren (2015) who empirically find that this effect does not apply for the Swedish market. However, when dividing the sample period into two regimes the coefficients on *hml* point in two different directions. In Panel B, *hml* has a negative and statistically significant effect on portfolio returns and in Panel C it has a positive and statistically significant effect.

As in the CAPM case, no clear distinction can be made between the top and bottom quintile. In addition to this setup, we have estimated the same regression models with different cut off points in time for the two regimes which provided results in line with those in Table 1 and Table 2.

4.1.1 Motivating a Regime Shift in Factor Returns

Table 7: Descriptive Statistics Factor Returns

Table 7 provides descriptive statistics for the market, size and value factor under different time regimes with the column year as the breaking point for the regime. Return0 constitutes the average return for the factor under the regime from 2006 until the column year. Return1 is the average return for the regime starting in the column year until late 2015.Vola0 is the volatility in the factor return under the regime from 2006 until the column year. Vola1 is the volatility in the factor return for the regime starting in the column year until late 2015.

Panel A: Market

	2008	2009	2010	2011	2012
return0	0.00022	-0.00053	-0.00001	0.00016	0.00005
return1	0.00025	0.00057	0.00041	0.00034	0.00055
vola0	0.01222	0.01742	0.01728	0.01629	0.01640
vola1	0.01451	0.01251	0.01162	0.01158	0.00968

Panel B: Size

	2008	2009	2010	2011	2012
return0	0.00003	-0.00008	0.00029	0.00029	0.00030
return1	0.00053	0.00064	0.00052	0.00057	0.00063
vola0	0.00710	0.01045	0.01083	0.01009	0.00992
vola1	0.00903	0.00787	0.00700	0.00708	0.00644

Panel C: Value

	2008	2009	2010	2011	2012
return0	-0.00024	-0.00034	0.00003	0.00002	0.00003
return1	-0.00005	0.00002	-0.00016	-0.00019	-0.00026
vola0	0.00453	0.00583	0.00746	0.00709	0.00683
vola1	0.00662	0.00645	0.00539	0.00538	0.00536

In Table 7, Panel A, the financial crisis in 2008 has a severe impact on the volatility in market returns in the different time regimes which is in line with the reasoning the results presented by Lindblom, Mavruk & Sjögren (2015), and we base our analysis on the 2009 regime, i.e. regime0 is for 2006-2008 and regime1 is for 2009-2015, which suggest a greater volatility in market return in regime0 compared to regime1.

Vola0 and Vola1 are the volatility in factor returns for different time regimes. In Panel A, in the 2008 column, Vola0 is the volatility in the market return between 2006 and late 2007 and Vola1 is the volatility for the market return between 2008 and late 2015. In the 2009 column vola0 is the volatility in market returns between late 2006 and 2008 and Vola1 is the volatility for the market return between 2009 and late 2015 and so on.

In Panel A, in the 2008 column, vola0 is lower compared to vola1, meaning that the volatility in market returns is lower for the regime before the crisis. For the other columns, when including the crisis in regime1, we see that the effect of the crisis is consistent and that volatility in market returns remains stable in the subsequent years after the crisis, i.e. vola0 is lower than vola1, which in turn suggests that the effect of the crisis on market volatility neither is leading nor lagging the actual event.

Panel B provides similar insights as Panel A suggesting that the volatility in the book-to-market factor is greater when the crisis is included in the time regime. Panel C show the same tendency but not the strong relationship as with the volatility in the market and size factor in Panel A and Panel B.

To control for this instability in parameters and to capture the impact of the crisis we utilize maximum likelihood estimation and estimate a Markov switching regression model using the Movestay command in Stata presented in Table 8 and Table 9.

4.1.2 AFP Robustness Analysis

Table 8: FF3 AFP Markov Regime Switch

We form quintile portfolios based on fund AFP scores and estimate the Fama & French three-factor time series regression model. The quintile portfolios are formed and rebalanced 10 weeks after each quarter from the first quarter in 2006 to the fourth quarter in 2015. Quintile 5 is the portfolio consisting of funds with the highest AFP score. Due to instability in parameters we utilize maximum likelihood estimation to estimate Markov switching regression model using the Movestay command in Stata. We allow for partial correlation between returns and the standard errors are clustered within quarters. Standard errors are presented in brackets and ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively. Starting with quintile 5 and going downwards in the table, the output for the difference between q5 and q1 is presented at the bottom. Regime0 is the between the years 2006-2008 and regime1 is for the years 2009-2015. The quintiles are named q1 to q5 with a 0 or 1 suffix to indicate the time regime.

VARIABLES	q50	q51	sigma0	sigma1	rho0	rho1
mkt	0.9737***	0.9394***	0,008	0,005	-0,558	-0,120
	(0.0296)	(0.0249)	0,001	0,001	0,123	0,313
smb	0.4114***	0.3168***				
	(0.0512)	(0.0392)				
hml	-0.1959***	0.0704*				
	(0.0712)	(0.0393)				
Constant	-0.0052***	0.0002				
	(0.0013)	(0.0009)				

VARIABLES	q40	q41	sigma0	sigma1	rho0	rho1
mkt	1.0531***	0.9717***	0,010	0,006	0,808	0,467
	(0.0092)	(0.0179)	0,001	0,001	0,037	0,151
smb	0.4126***	0.3379***				
	(0.0362)	(0.0405)				
hml	-0.1300***	0.0733*				
	(0.0477)	(0.0432)				
Constant	0.0090***	-0.0014**				
	(0.0013)	(0.0006)				

VARIABLES	q30	q31	sigma0	sigma1	rho0	rho1
mkt	1.0588***	0.9342***	0,009	0,006	0,785	-0,398
	(0.0213)	(0.0481)	0,001	0,001	0,036	1,080
smb	0.3244***	0.2403***				
	(0.0415)	(0.0451)				
hml	-0.1414***	0.1116***				
	(0.0388)	(0.0262)				
Constant	0.0083***	0.0008				
	(0.0013)	(0.0032)				

VARIABLES	q20	q21	sigma0	sigma1	rho0	rho1
mkt	1.0202***	0.9060***	0,009	0,006	0,759	0,499
	(0.0033)	(0.0347)	0,002	0,001	0,043	0,177
smb	0.3667***	0.2362***				
	(0.0151)	(0.0247)				
hml	-0.1537***	0.1068***				
	(0.0505)	(0.0243)				
Constant	0.0084***	-0.0014**				
	(0.0016)	(0.0005)				

VARIABLES	q10	q11	sigma0	sigma1	rho0	rho1
mkt	0.9984***	0.9497***	0,008	0,005	0,703	-0,075
	(0.0222)	(0.0182)	0,001	0,001	0,093	0,039
smb	0.3446***	0.3606***				
	(0.0360)	(0.0378)				
hml	-0.1038***	0.0653**				
	(0.0397)	(0.0280)				
Constant	0.0069***	0.0001				
	(0.0017)	(0.0002)				

VARIABLES	Topminusbottom0	Topminusbottom1	sigma0	sigma1	rho0	rho1
mkt	0.2428	-0.0081**	0,028	0,004	-1,000	0,234
	(0.2515)	(0.0041)	0,001	0,000	.	0,096
smb	0.3546	-0.0402				
	(0.3424)	(0.0280)				
hml	0.0807	0.0048				
	(0.1325)	(0.0213)				
Constant	-0.0347***	-0.0004*				
	(0.0016)	(0.0002)				

For all portfolios the coefficient of the MKT factor has a positive sign and statistically significant effect on portfolio performance, however with a greater economic significance for the first regime with levels close to 1 and around 0.9 for the second regime respectively. This result suggests a lower market risk premium during the first time period.

When searching for differences between the top AFP portfolio and the bottom AFP portfolio in Table 8 we retrieve negative and statistically significant alphas for both regimes, but at a higher significance level for regime0. This suggest that funds with high AFP underperform relatively to low AFP funds before and after the crisis, which stands in contrast with the results obtained by Jiang and Zheng. The level of the risk adjusted abnormal return under regime0 cannot be explained by any means and we need to nuance the specification additionally.

Looking at the individual portfolio regression coefficients and starting with the two opposites, quintile 5 provides a significant negative alpha for regime0 and an insignificant positive alpha for regime1. For quintile 1 however, we retrieve a positive and significant alpha at under the first regime and a positive but insignificant alpha under the second regime. No further insights in line with Jiang and Zheng's findings are provided when looking at the quintiles in between q5 and q1. Quintile 2, 3 and 4 provide positive and significant alphas for the first regime but points in different directions in the second regime.

The coefficient of the SMB factor ranges from 0.32 to 0.41 in regime0 and the top quintiles are experiencing a greater magnitude of the factor exposure compared to bottom portfolios. However, the difference between the two the topminusbottom specification provides statistically insignificant results. This does not hold for regime1. No clear distinction between top and bottom portfolios can be made in terms of SMB exposure and the coefficients overall are at lower levels ranging from 0.23 to 0.36. The coefficients of the SMB factor on portfolio returns show a greater economic significance for regime0 compared to regime1 meaning that the risk premium of the spread between small and large stocks before for the time period 2006-2008 is greater.

The HML factor differs between regimes. For regime0 the book-to-market premium has a negative effect on portfolio return and a positive effect for regime1. Earlier findings in the Swedish market such as Lindblom, Mavruk and Sjögren (2015) suggest that the HML factor has a negative but statistically insignificant effect, which does not apply to our results.

In line with descriptive statistics on factor returns in Table 7, the sigma0 is greater than sigma1 for all quintiles, suggesting a larger variation in portfolio returns in regime0 compared to regime1.

Table 9: FF3 AFP Markov Regime Switch Trend

Following the methodology for the specification in Table 8 we extend the testing of parameter instability. In addition to utilizing maximum likelihood estimation in order to estimate Markov switching regression model we include a trend variable to capture the cumulative effect of the crisis. We allow for partial correlation between returns and the standard errors are clustered within quarters. Standard errors are presented in brackets and ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively. Starting with quintile 5 and going downwards in the table, the output for the difference between q5 and q1 is presented at the bottom. Regime0 is the between the years 2006-2008 and regime1 is for the years 2009-2015. The quintiles are named q1 to q5 with a 0 or 1 suffix to indicate the time regime.

VARIABLES	q50	q51	sigma0	sigma1	rho0	rho1
mkt	1.0094***	0.9432***	0,007	0,005	-0,092	-0,105
	(0.0221)	(0.0152)	0,001	0,001	0,063	0,021
smb	0.4719***	0.3235***				
	(0.0367)	(0.0238)				
hml	-0.1885***	0.0724***				
	(0.0450)	(0.0216)				
trend	-0.0000	0.0000				
	(0.0001)	(0.0000)				
Constant	0.0001	-0.0003				
	(0.0006)	(0.0004)				

VARIABLES	q40	q41	sigma0	sigma1	rho0	rho1
mkt	1.0562***	0.9721***	0,0096	0,006	0,81	0,47
	(0.0286)	(0.0168)	0,001	0,006	0,03	0,15
smb	0.4177***	0.3388***				
	(0.0471)	(0.0265)				
hml	-0.1290**	0.0743***				
	(0.0527)	(0.0233)				
trend	0.0001	0.0000				
	(0.0001)	(0.0000)				
Constant	0.0088***	-0.0017***				
	(0.0009)	(0.0006)				

VARIABLES	q30	q31	sigma0	sigma1	rho0	rho1
mkt	0.9984***	0.9449***	0,007	0,005	0,051	0,023
	(0.0220)	(0.0154)	0,0007	0,0006	0,075	0,039
smb	0.2198***	0.2583***				
	(0.0365)	(0.0241)				
hml	-0.1531***	0.1160***				
	(0.0447)	(0.0218)				
trend	-0.0000	0.0000				
	(0.0001)	(0.0000)				
Constant	0.0003	-0.0003				
	(0.0006)	(0.0004)				

VARIABLES	q20	q21	sigma0	sigma1	rho0	rho1
mkt	0.9585***	0.8888***	0,0072	0,0054	0,16	-0,0015
	(0.0237)	(0.0154)	0,001	0,004	0,18	0,0399
smb	0.2687***	0.2053***				
	(0.0395)	(0.0240)				
hml	-0.1715***	0.1015***				
	(0.0483)	(0.0217)				
trend	-0.0000	0.0000				
	(0.0001)	(0.0000)				
Constant	0.0001	-0.0001				
	(0.0006)	(0.0004)				

VARIABLES	q10	q11	sigma0	sigma1	rho0	rho1
mkt	0.9502***	0.9522***	0,006	0,005	-0,005	-0,005
	(0.0216)	(0.0156)	0,0007	0,0005	0,021	0,045
smb	0.2617***	0.3646***				
	(0.0359)	(0.0243)				
hml	-0.1119**	0.0658***				
	(0.0440)	(0.0220)				
trend	0.0000	-0.0000				
	(0.0001)	(0.0000)				
Constant	0.0001	0.0000				
	(0.0006)	(0.0005)				

VARIABLES	topminusbottom0	topminusbottom1	sigma0	sigma1	rho0	rho1
mkt	0.0592***	-0.0100	0,005	0,003	0	-1
	(0.0163)	(0.0108)	0,0005	.	0,053	.
smb	0.2104***	-0.0425**				
	(0.0271)	(0.0169)				
hml	-0.0767**	0.0052				
	(0.0331)	(0.0153)				
trend	-0.0000	0.0000				
	(0.0001)	(0.0000)				
Constant	0.0000	-0.0001				
	(0.0004)	(0.0003)				

We keep the same framework as in Table 8 but include a trend variable based on quarters. The reasoning behind the inclusion of a trend is to capture the cumulative effect of the economic shock associated with the financial crisis in 2008. The trend variable is assigned the value of 1 for the first quarter in 2006 and ranges to 39 for the fourth quarter in 2015.

For quintile 3 and quintile 2 we observe statistically significant coefficients for the trend variable under regime1. However, the effect is economically insignificant and close to zero. For the remaining quintiles under both regime0 and regime1 we retrieve economically and statistically insignificant results.

Comparing the results in Table 9 to the output in Table 8 in which no trend variable is included, we conclude that the inclusion of the trend variable removes the statistically significant alphas from all specifications for regime0. Despite the insignificant coefficient of the trend variable itself, it still captures the partial correlation between the trend variable and the remaining explanatory variables.

The coefficients on the factor returns behave in the same manner as in the previous specification in Table 8. The coefficients on SMB returns are positive and statistically significant for all quintiles. However, the differences between regime0 and regime1 across quintiles point in different directions when it comes to magnitude, suggesting that the premium for investing small cap stocks is larger in regime0 than in regime1 for some quintiles and vice versa for some quintiles. The same holds for the HML factors. The premium for investing in value stocks is similar as the one in Table 8 when it comes to magnitude and significance. The effect is negative under regime0 and positive for regime1.

4.2 Active Share Framework

Cremers & Petajisto (2009) works as a foundation when we investigate the statistical relationship between active management and risk-adjusted performance by calculating Active Share and subsequently ranking and forming quintile portfolios based on this characteristic. The active share regression is specified in the same way as in the AFP specifications. In Table 10 and 11 we perform the same analysis as for the AFP specifications but we form portfolios based on the funds' active share. For Table 11, we control for endogenous regime switching caused by the financial crisis using the Movestay command in Stata.

Table 10: CAPM Active Share

In Table 10 we form quintile portfolios based on funds Active Share score and estimate the CAPM time series regression model. The quintile portfolios are formed and rebalanced 10 weeks after each quarter from the first quarter in 2006 to the fourth quarter in 2015. Quintile 5 is the portfolio consisting of funds with the highest Active Share score. In panel A we regress each portfolio return on the market factor for the entire time period, panel B for the time period 2006-2008 and panel C for the time period 2009-2015. We allow for partial correlation between returns and the standard errors are clustered within quarters[8]. Standard errors are presented in parenthesis and ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A : 2006-2015

VARIABLES	q5	q4	q3	q2	q1	topminusbottom
mkt	0.6753***	0.8037***	0.8477***	0.8631***	0.8689***	-0.1936***
	(0.0116)	(0.0064)	(0.0072)	(0.0110)	(0.0067)	(0.0159)
Constant	0.0001	0.0000	-0.0001*	-0.0000	-0.0001	0.0002
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Observations	2,374	2,374	2,374	2,373	2,374	2,374
R-squared	0.7337	0.8323	0.8518	0.8234	0.8694	0.3107

Panel B: 2006-2008

VARIABLES	q5	q4	q3	q2	q1	topminusbottom
mkt	0.6679***	0.8225***	0.8420***	0.8464***	0.8616***	-0.1937***
	(0.0166)	(0.0144)	(0.0136)	(0.0114)	(0.0062)	(0.0167)
Constant	-0.0003	-0.0002	-0.0002	-0.0001*	-0.0001*	-0.0002
	(0.0002)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0002)
Observations	685	685	685	685	685	685
R-squared	0.7247	0.8399	0.8613	0.8286	0.8727	0.2993

Panel C: 2009-2015

VARIABLES	q5	q4	q3	q2	q1	topminusbottom
mkt	0.6796***	0.7883***	0.8518***	0.8758***	0.8745***	-0.1949***
	(0.0209)	(0.0162)	(0.0072)	(0.0098)	(0.0108)	(0.0253)
Constant	0.0003	0.0001	-0.0000	0.0000	-0.0000	0.0004*
	(0.0002)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Observations	1,689	1,689	1,689	1,688	1,689	1,689
R-squared	0.7403	0.8260	0.8442	0.8196	0.8667	0.3246

In Table 10 the CAPM specification provides results similar to the results in Table 5, with the exception of lower beta coefficients for quintile 5 in all panels. Statistically significant difference on the constant between the top and bottom portfolio is found in Panel C, however since the constant of quintile 5 and quintile 1 separately are not statistically significant, the positive alpha cannot be interpreted as being in line with the findings of Jiang & Zheng (2015).

[8] Stata does not provide an F-statistic after a clustered regression due to the usage of Huber variances (www.stata.com/statalist). In the Regression Output Appendix unclustured regressions with F-Statistic are presented for both the AFP and the Active Share framework.

Table 11: FF3 Active Share

In Table 11 we form quintile portfolios based on funds' Active Share score and estimate the Fama & French three-factor time series regression model. The quintile portfolios are formed and rebalanced 10 weeks after each quarter from the first quarter in 2006 to the fourth quarter in 2015. Quintile 5 is the portfolio consisting of funds with the highest Active Share score. In panel A we regress each portfolio return on the market factor for the entire time period, panel B for the time period 2006-2008 and panel C for the time period 2009-2015. We allow for partial correlation between returns and the standard errors are clustered within quarters. Standard errors are presented in brackets and ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A : 2006-2015

VARIABLES	q5	q4	q3	q2	q1	topminusbottom
mkt	0.9241***	0.9468***	0.9392***	0.9564***	0.9458***	-0.0217
	(0.0167)	(0.0107)	(0.0140)	(0.0196)	(0.0123)	(0.0150)
smb	0.5527***	0.3247***	0.2035***	0.2131***	0.1763***	0.3765***
	(0.0317)	(0.0378)	(0.0246)	(0.0324)	(0.0292)	(0.0192)
hml	-0.0419*	0.0032	-0.0141	0.0076	0.0080	-0.0500**
	(0.0165)	(0.0262)	(0.0249)	(0.0255)	(0.0249)	(0.0152)
Constant	-0.0002	-0.0002	-0.0002*	-0.0001	-0.0002	-0.0000
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	2,374	2,374	2,374	2,373	2,374	2,374
R-squared	0.8250	0.8574	0.8609	0.8327	0.8761	0.5313

Panel B: 2006-2008

VARIABLES	q5	q4	q3	q2	q1	topminusbottom
mkt	0.9486***	0.9764***	0.9437***	0.9444***	0.9419***	0.0067
	(0.0142)	(0.0024)	(0.0187)	(0.0214)	(0.0070)	(0.0179)
smb	0.6338***	0.3448***	0.2224***	0.2151***	0.1762***	0.4576***
	(0.0341)	(0.0142)	(0.0142)	(0.0165)	(0.0174)	(0.0440)
hml	-0.1513*	-0.1176*	-0.1428*	-0.1252	-0.1063	-0.0450
	(0.0515)	(0.0406)	(0.0558)	(0.0548)	(0.0486)	(0.0268)
Constant	-0.0002	-0.0001	-0.0002	-0.0001	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	685	685	685	685	685	685
R-squared	0.8326	0.8647	0.8726	0.8384	0.8794	0.5764

Panel C: 2009-2015

VARIABLES	q5	q4	q3	q2	q1	topminusbottom
mkt	0.9122***	0.9257***	0.9397***	0.9704***	0.9526***	-0.0404
	(0.0118)	(0.0252)	(0.0159)	(0.0178)	(0.0148)	(0.0209)
smb	0.5102***	0.3258**	0.2063***	0.2287**	0.1917***	0.3185***
	(0.0185)	(0.0625)	(0.0329)	(0.0407)	(0.0325)	(0.0254)
hml	-0.0166	0.0540**	0.0285**	0.0494**	0.0476*	-0.0642
	(0.0167)	(0.0142)	(0.0063)	(0.0140)	(0.0196)	(0.0355)
Constant	0.0000	-0.0002	-0.0002*	-0.0002	-0.0002*	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	1,689	1,689	1,689	1,688	1,689	1,689
R-squared	0.8219	0.8536	0.8538	0.8307	0.8751	0.5065

The Fama-French three factor specification in Table 11 overall resembles the same specification as in Table 6. The R-squared coefficient is slightly higher for all regressions in comparison to the AFP setup, ranging from 0.82 to 0.87. The coefficients on the market factor are showing the same patterns of statistical significance, but deviates from the traditional AFP specification when it comes to magnitude, as it is smaller for all quintiles compared to AFP specification.

Regarding the size factor, the active share specification in Table 11 differs from the traditional AFP specification in Table 7. In this specification the size coefficient is exhibiting greater differences between the top and bottom portfolio and with incremental increase in factor exposure from the bottom quintile to the top quintile.

The size exposures for quintile 5 in the three different panels are 0.553, 0.634 and 0.510 respectively and all statistically significant. For the bottom quintile, the size exposures are 0.176, 0.176 and 0.192 respectively. This result suggests that funds with a higher active share are investing more in small cap stocks compared to funds with a lower active share. In addition to this, in line with the results in the AFP specification, the SMB coefficients in Table 11 are generally higher under the regime0 compared to regime1. In Table 7 descriptive statistics on factors returns are provided. In the 2009 column we conclude that the average return for regime0 is lower than the average return in regime1 speaking in favor for a lower premium for investing in small caps stocks in regime0 compared to regime1 and thus overall lower SMB coefficients for all quintiles. Moreover, a potential explanation to lower economic significance is overall reduced exposure to that type of stock regardless of the degree of activeness for the fund.

No positive or statistically significant alphas were retrieved in any specification or regime. Quintile 3 and quintile 1 yield low negative alpha significant at a 10 percent significance level.

4.2.1 Active Share Robustness Analysis

Table 12: FF3 Active Share Markov Regime Switch

In Table 12 we form quintile portfolios based on funds Active Share score and estimate the Fama & French three-factor time series regression model. The quintile portfolios are formed and rebalanced 10 weeks after each quarter from the first quarter in 2006 to the fourth quarter in 2015. Quintile 5 is the portfolio consisting of funds with the highest Active Share score. Due to instability in parameters we utilize maximum likelihood estimation in order to estimate Markov switching regression model using the Movestay command in Stata. We allow for partial correlation between returns and the standard errors are clustered within quarters. Standard errors are presented in brackets and ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively. The quintiles are named q1 to q5 with a 0 or 1 suffix to indicate the time regime.

VARIABLES	q50	q51	sigma0	sigma1	rho0	rho1
mkt	0.9160***	0.9005***	0,006	0,004	-0,575	-0,429
	(0.0189)	(0.0442)	0,001	0,001	0,178	0,551
smb	0.5802***	0.4902***				
	(0.0333)	(0.0715)				
hml	-0.1592***	-0.0200				
	(0.0616)	(0.0155)				
Constant	-0.0045**	0.0007				
	(0.0021)	(0.0012)				
VARIABLES	q40	q41	sigma0	sigma1	rho0	rho1
mkt	-0.3780	1.0177***	0,055	0,015	0,970	-1,000
	(0.0000)	(0.0002)	0,428	0,001	0,224	.
smb	-0.3581	0.3594***				
	(10.6692)	(0.0002)				
hml	0.4493	-0.0409***				
	(3.4885)	(0.0001)				
Constant	0.0551	0.0094***				
	(0.3986)	(0.0004)				
VARIABLES	q30	q31	sigma0	sigma1	rho0	rho1
mkt	0.9968***	0.9388***	0,008	0,004	0,790	-0,033
	(0.0304)	(0.0168)	0,001	0,000	0,023	0,038
smb	0.3080***	0.2046***				
	(0.0243)	(0.0339)				
hml	-0.1320***	0.0282***				
	(0.0463)	(0.0063)				
Constant	0.0069***	-0.0001				
	(0.0010)	(0.0002)				
VARIABLES	q20	q21	sigma0	sigma1	rho0	rho1
mkt	0.9995***	0.9698***	0,009	0,005	0,754	-0,020
	(0.0279)	(0.0188)	0,001	0,000	0,067	0,047
smb	0.3058***	0.2277***				
	(0.0241)	(0.0421)				
hml	-0.1127**	0.0492***				
	(0.0460)	(0.0145)				
Constant	0.0075***	-0.0001				
	(0.0008)	(0.0002)				
VARIABLES	q10	q11	sigma0	sigma1	rho0	rho1
mkt	0.9864***	0.9518***	0,007	0,004	0,722	-0,031
	(0.0136)	(0.0152)	0,001	0,000	0,044	0,044
smb	0.2491***	0.1903***				
	(0.0117)	(0.0332)				
hml	-0.0945**	0.0474**				
	(0.0387)	(0.0199)				
Constant	0.0060***	-0.0002				
	(0.0007)	(0.0001)				
VARIABLES	topminusbottom0	topminusbottom1	sigma0	sigma1	rho0	rho1
mkt	-0.7824**	-0.0011	0,068	0,010	-0,984	-1,000
	(0.3825)	(0.2191)	0,035	0,002	0,015	.
smb	-2.2871	0.2501				
	(0.0000)	(0.4248)				
hml	0.0178	-0.0101				
	(0.5649)	(0.1923)				
Constant	-0.0701**	0.0060***				
	(0.0303)	(0.0006)				

In Table 12 the differences in the coefficients on factor returns between regimes are consistent with the results obtained in the AFP specification in Table 7. The incremental difference between the quintiles, as observed in Table 11 remains in the Markov regime switch specification and characterizes the difference between a high and a low active share profile.

In addition, when incorporating the results from the CAPM specification in Table 10, quintile 5 is experiencing a substantially lower beta coefficient than quintiles with a lower active share rank. This in combination with a positive and statistically significant alpha for quintile 1 in regime0 and a negative statistically significant alpha for quintile 5 supports the reasoning that stock picking is inferior to allocation in financial turmoil and that active funds, that seeks marginal return underperform relative to less active funds in times of crisis (Kacperczyk, Van Nieuwerburgh, Veldkamp, 2014).

The quintile 5 negative alpha and the quintile 1 positive alpha in the first regime are in line with the findings of Barber & Odean (2000) that active investors underperform relative to the market. As for regime1, the positive alpha cannot be confirmed since quintile 5 and 1 do not exhibit statistical significance alphas individually.

The HML factors give no clear indication as in previous specification and are statistically significant in some of the panels and are generally negative in the first regime and positive in the second regime. The magnitude and economic significance cannot be derived to portfolios sorted based on the funds degree of activeness. The coefficients on factor returns in the q4 panel under the first time regime cannot be motivated by any means. However for the second regime, the market, size and price-to-book exposures are all statistically significant.

Following the same reasoning as for the specification in Table 9, when including a trend variable to capture the cumulative effect of the economic shock in 2008, the significant risk-adjusted returns for some quintiles in Table 12 disappear which is similar to the results in Table 9 and the effect of the inclusion of a trend variable as becomes evident in Table A-9 in Regression Output Appendix.

5 Conclusions & Implications

This thesis examines the performance of active fund management in Sweden 2006-2015 by applying an identification framework for mutual fund managers. The Active Fundamental Performance (AFP) measure, proposed by Jiang & Zheng (2015), is defined as covariance between deviations from market weights and three-day alpha around earnings announcements. The first hypothesis was that funds ranked in the top quintile would outperform those in the bottom quintile. Our results show that the top quintile portfolio exhibit statistically significant negative alphas during the financial crisis and alphas not different from zero afterwards. The second hypothesis was that funds would rank persistently in the top or bottom quintile. We find no persistence in the measure, fund managers ranking in the top quintile AFP do not remain there with any margin in the subsequent quarters and those ranking in the bottom quintile do not remain in the bottom quintile. The third hypothesis was that the factor coefficients would have varying volatility over the sample time period. We confirm this hypothesis as we observe parameter instability in the factor coefficients with increased volatility in the two years before and including the financial crisis compared to the years after 2008. This is consistent with Lindblom, Mavruk & Sjögren (2015).

The fourth hypothesis was that funds in the top quintile Active Share would outperform those in the bottom quintile, based on the study by Cremers & Petajisto (2009). We find that this hypothesis does not hold for our sample. The results are overall in line with the results found for the AFP portfolios. These findings taken together support the efficient market hypothesis and should be taken as advice that, without any special preferences or outside positions (Sharpe, 2007); a passive investment strategy is preferred. Reasons as to why our results differ from the studies of Jiang & Zheng and Cremers & Petajisto may be derived to the significantly greater number of domestic stocks in the US. This allows funds to focus on specific sectors or niches while still being sufficiently diversified, whereas in Sweden there are fewer firms to choose from within each sector. Thus there is a trade-off between deviating from the benchmark and diversifying. The Swedish capital market is highly developed while being relatively small in size, which would speak in favor of market efficiency.

The main implication of our findings is that a passive investment vehicle would yield better returns than their active counterparts and be a better investment decision for most investors. This aligns well with Sharpe's and several others' advice of focusing on allocation and individual's outside positions and preferences rather than trying to outsmart the market. The results from our regressions reinforce the reasoning put forward by Kacperczyk, Van Nieuwerburgh & Veldkamp (2014) that stock picking is inferior to allocation in financial turmoil and that active funds, seeking marginal returns underperform more relatively to less active funds in times of crisis.

The study has constructed a framework offering many additional areas to investigate, the structuring of fund holdings offer a platform to branch out from. Manager styles and characteristics with regards to holdings as well as factors such as fund flows, turnover rate etc. could refine the ranking algorithm. Expanding the geographical scope to the full Nordic or European market could address our remarks of Sweden's rather small investment universe and large mutual fund industry as well as enable further comparability with Jiang & Zheng's (2015) larger US sample.

As for the AFP framework we set out to research in Sweden, the approach has an intuitive appeal, but has no firm roots in theoretical studies. It leaves the managers' investment decisions as a black box and has an implied assumption that the fund managers will be persistent in their performance. Proposing that deviation from the mean-variance efficient frontier can generate superior risk-adjusted returns implies that the frontier is not efficient to start with. The hypothesis of outperformance thus fails to reconcile with Fama's (1970) efficient market hypothesis, which quite naturally made it a candidate for testing. As Sharpe stated in "The Arithmetic of Active Management", even if active management underperforms on average due to its costs, there may be funds that outperform. The challenge is to identify these. Jiang & Zheng show that the AFP framework can succeed in this on their US sample, but based on our findings in Sweden 2006-2015, the AFP framework is not the approach to use.

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Appendix

Regression Output Appendix

Table A-1 AFP CAPM

We form quintile portfolios based on funds' AFP score and estimate the CAPM time series regression model. The portfolios are formed and rebalanced 10 weeks after each quarter from the first quarter in 2006 the fourth quarter in 2015. Quintile 5 is the portfolio consisting of funds with the highest AFP score. In panel A we regress each portfolio return on the market factor for the entire time period, panel B for the time period 2006-2008 and panel C for the time period 2009-2015. Standard errors are presented in parenthesis and ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: 2006-2015

VARIABLES	q5	q4	q3	q2	q1	Topminusbottom
mkt	0.8049***	0.8376***	0.8701***	0.8237***	0.8139***	-0.0089
	(0.0091)	(0.0092)	(0.0088)	(0.0090)	(0.0090)	(0.0060)
Constant	0.0001	0.0001	0.0001	0.0001	0.0002	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	2,374	2,374	2,374	2,374	2,374	2,374
R-squared	0.7663	0.7780	0.8049	0.7792	0.7765	0.0009
F-Stat	7780	8311	9788	8370	8243	2.209
Prob > F	0	0	0	0	0	0.137

Panel B: 2006-2008

VARIABLES	q5	q4	q3	q2	q1	Topminusbottom
mkt	0.7977***	0.8501***	0.8977***	0.8359***	0.8323***	-0.0346***
	(0.0166)	(0.0161)	(0.0152)	(0.0165)	(0.0151)	(0.0114)
Constant	-0.0003	-0.0001	0.0000	-0.0001	0.0000	-0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)
Observations	685	685	685	685	685	685
R-squared	0.7722	0.8032	0.8369	0.7895	0.8174	0.0133
F-Stat	2316	2788	3504	2562	3057	9.237
Prob > F	0	0	0	0	0	0.00246

Panel C: 2009-2015

VARIABLES	q5	q4	q3	q2	q1	Topminusbottom
mkt	0.8095***	0.8271***	0.8481***	0.8134***	0.7989***	0.0107
	(0.0110)	(0.0114)	(0.0110)	(0.0108)	(0.0114)	(0.0070)
Constant	0.0002	0.0002	0.0002	0.0002	0.0002*	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	1,689	1,689	1,689	1,689	1,689	1,689
R-squared	0.7615	0.7578	0.7794	0.7705	0.7448	0.0014
F-Stat	5385	5279	5959	5662	4923	2.308
Prob > F	0	0	0	0	0	0.129

Table A-2 AFP FF3

We form quintile portfolios based on funds AFP score and estimate the Fama & French three-factor time series regression model. The quintile portfolios are formed and rebalanced 10 weeks after each quarter from the first quarter in 2006 the fourth quarter in 2015. Quintile 5 is the portfolio consisting of funds with the highest AFP score. In panel A we regress each portfolio return on the market factor for the entire time period, panel B for the time period 2006-2008 and panel C for the time period 2009-2015. Standard errors are presented in brackets and ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: 2006-2015

VARIABLES	q5	q4	q3	q2	q1	Topminusbottom
mkt	0.9680***	0.9681***	0.9684***	0.9174***	0.9515***	0.0165*
	(0.0124)	(0.0129)	(0.0125)	(0.0128)	(0.0124)	(0.0088)
smb	0.3716***	0.2965***	0.2301***	0.2186***	0.3130***	0.0586***
	(0.0198)	(0.0205)	(0.0199)	(0.0205)	(0.0199)	(0.0140)
hml	0.0124	0.0066	0.0321	0.0272	0.0076	0.0048
	(0.0198)	(0.0204)	(0.0199)	(0.0204)	(0.0198)	(0.0139)
Constant	-0.0001	-0.0001	-0.0000	0.0000	0.0000	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	2,374	2,374	2,374	2,374	2,374	2,374
R-squared	0.7965	0.7960	0.8155	0.7895	0.7977	0.0084
F-Stat	3092	3082	3492	2962	3116	6.653
Prob > F	0	0	0	0	0	0.000180

Panel B: 2006-2008

VARIABLES	q5	q4	q3	q2	q1	Topminusbottom
mkt	0.9432***	0.9551***	0.9448***	0.8887***	0.9522***	-0.0090
	(0.0153)	(0.0159)	(0.0154)	(0.0154)	(0.0156)	(0.0102)
smb	0.3233***	0.3090***	0.2578***	0.2050***	0.3648***	-0.0414***
	(0.0238)	(0.0248)	(0.0241)	(0.0240)	(0.0243)	(0.0159)
hml	0.0717***	0.0678***	0.1150***	0.1009***	0.0662***	0.0055
	(0.0215)	(0.0224)	(0.0218)	(0.0217)	(0.0220)	(0.0144)
Constant	-0.0001	-0.0001	-0.0001	0.0000	-0.0001	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	1,689	1,689	1,689	1,689	1,689	1,689
R-squared	0.7856	0.7788	0.7957	0.7820	0.7752	0.0056
F-Stat	2058	1978	2188	2015	1937	3.136
Prob > F	0	0	0	0	0	0.0246

Panel C: 2009-2015

VARIABLES	q5	q4	q3	q2	q1	Topminusbottom
mkt	0.9432***	0.9551***	0.9448***	0.8887***	0.9522***	-0.0090
	(0.0153)	(0.0159)	(0.0154)	(0.0154)	(0.0156)	(0.0102)
smb	0.3233***	0.3090***	0.2578***	0.2050***	0.3648***	-0.0414***
	(0.0238)	(0.0248)	(0.0241)	(0.0240)	(0.0243)	(0.0159)
hml	0.0717***	0.0678***	0.1150***	0.1009***	0.0662***	0.0055
	(0.0215)	(0.0224)	(0.0218)	(0.0217)	(0.0220)	(0.0144)
Constant	-0.0001	-0.0001	-0.0001	0.0000	-0.0001	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	1,689	1,689	1,689	1,689	1,689	1,689
R-squared	0.7856	0.7788	0.7957	0.7820	0.7752	0.0056
F-Stat	2058	1978	2188	2015	1937	3.136
Prob > F	0	0	0	0	0	0.0246

Table A-3 – Active Share CAPM

We form quintile portfolios based on funds' Active Share score and estimate the CAPM time series regression model. The quintile portfolios are formed and rebalanced 10 weeks after each quarter from the first quarter in 2006 the fourth quarter in 2015. Quintile 5 is the portfolio consisting of funds with the highest Active Share score. In panel A we regress each portfolio return on the market factor for the entire time period, panel B for the time period 2006-2008 and panel C for the time period 2009-2015.. Standard errors are presented in parenthesis and ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: 2006-2015

VARIABLES	q5	q4	q3	q2	q1	Topminusbottom
mkt	0.6753***	0.8037***	0.8477***	0.8631***	0.8689***	-0.1936***
	(0.0084)	(0.0074)	(0.0073)	(0.0082)	(0.0069)	(0.0059)
Constant	0.0001	0.0000	-0.0001	-0.0000	-0.0001	0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	2,374	2,374	2,374	2,373	2,374	2,374
R-squared	0.7337	0.8323	0.8518	0.8234	0.8694	0.3107
F-Stat	6537	11770	13632	11056	15797	1069
Prob > F	0	0	0	0	0	0

Panel B: 2006-2008

VARIABLES	q5	q4	q3	q2	q1	Topminusbottom
mkt	0.6679***	0.8225***	0.8420***	0.8464***	0.8616***	-0.1937***
	(0.0158)	(0.0137)	(0.0129)	(0.0147)	(0.0126)	(0.0113)
Constant	-0.0003	-0.0002	-0.0002	-0.0001	-0.0001	-0.0002
	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Observations	685	685	685	685	685	685
R-squared	0.7247	0.8399	0.8613	0.8286	0.8727	0.2993
F-Stat	1798	3584	4243	3302	4682	291.7
Prob > F	0	0	0	0	0	0

Panel C: 2009-2015

VARIABLES	q5	q4	q3	q2	q1	Topminusbottom
mkt	0.6796***	0.7883***	0.8518***	0.8758***	0.8745***	-0.1949***
	(0.0098)	(0.0088)	(0.0089)	(0.0100)	(0.0083)	(0.0068)
Constant	0.0003	0.0001	-0.0000	0.0000	-0.0000	0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	1,689	1,689	1,689	1,688	1,689	1,689
R-squared	0.7403	0.8260	0.8442	0.8196	0.8667	0.3246
F-Stat	4810	8009	9141	7657	10971	810.7
Prob > F	0	0	0	0	0	0

Table A-4 – Active Share FF3

We form quintile portfolios based on funds' Active Share score and estimate the Fama & French three-factor time series regression model. The quintile portfolios are formed and rebalanced 10 weeks after each quarter from the first quarter in 2006 the fourth quarter in 2015. Quintile 5 is the portfolio consisting of funds with the highest Active Share score. In panel A we regress each portfolio return on the market factor for the entire time period, panel B for the time period 2006-2008 and panel C for the time period 2009-2015. Standard errors are presented in brackets and ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: 2006-2015

VARIABLES	q5	q4	q3	q2	q1	Topminusbottom
mkt	0.9241***	0.9468***	0.9392***	0.9564***	0.9458***	-0.0217***
	(0.0099)	(0.0100)	(0.0103)	(0.0117)	(0.0098)	(0.0071)
smb	0.5527***	0.3247***	0.2035***	0.2131***	0.1763***	0.3765***
	(0.0158)	(0.0159)	(0.0164)	(0.0186)	(0.0157)	(0.0114)
hml	-0.0419***	0.0032	-0.0141	0.0076	0.0080	-0.0500***
	(0.0157)	(0.0159)	(0.0164)	(0.0186)	(0.0157)	(0.0114)
Constant	-0.0002**	-0.0002*	-0.0002*	-0.0001	-0.0002	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	2,374	2,374	2,374	2,373	2,374	2,374
R-squared	0.8250	0.8574	0.8609	0.8327	0.8761	0.5313
F-Stat	3724	4748	4889	3930	5585	895.6
Prob > F	0	0	0	0	0	0

Panel B: 2006-2008

VARIABLES	q5	q4	q3	q2	q1	Topminusbottom
mkt	0.9486***	0.9764***	0.9437***	0.9444***	0.9419***	0.0067
	(0.0182)	(0.0187)	(0.0184)	(0.0212)	(0.0182)	(0.0131)
smb	0.6338***	0.3448***	0.2224***	0.2151***	0.1762***	0.4576***
	(0.0303)	(0.0311)	(0.0305)	(0.0353)	(0.0302)	(0.0217)
hml	-0.1513***	-0.1176***	-0.1428***	-0.1252***	-0.1063***	-0.0450*
	(0.0375)	(0.0385)	(0.0378)	(0.0436)	(0.0374)	(0.0269)
Constant	-0.0002	-0.0001	-0.0002	-0.0001	-0.0001	-0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Observations	685	685	685	685	685	685
R-squared	0.8326	0.8647	0.8726	0.8384	0.8794	0.5764
F-Stat	1129	1450	1555	1177	1655	308.9
Prob > F	0	0	0	0	0	0

Panel C: 2009-2015

VARIABLES	q5	q4	q3	q2	q1	Topminusbottom
mkt	0.9122***	0.9257***	0.9397***	0.9704***	0.9526***	-0.0404***
	(0.0118)	(0.0118)	(0.0126)	(0.0142)	(0.0118)	(0.0085)
smb	0.5102***	0.3258***	0.2063***	0.2287***	0.1917***	0.3185***
	(0.0185)	(0.0184)	(0.0196)	(0.0221)	(0.0184)	(0.0133)
hml	-0.0166	0.0540***	0.0285	0.0494**	0.0476***	-0.0642***
	(0.0167)	(0.0167)	(0.0178)	(0.0200)	(0.0167)	(0.0121)
Constant	-0.0002*	-0.0002*	-0.0002*	-0.0002	-0.0002**	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	1,689	1,689	1,689	1,688	1,689	1,689
R-squared	0.8219	0.8536	0.8538	0.8307	0.8751	0.5065
F-Stat	2592	3276	3281	2753	3936	576.4
Prob > F	0	0	0	0	0	0

Table A-5 - Persistent AFP CAPM

We form portfolios based on funds' persistency in their AFP score and estimate the CAPM time series regression model. The portfolios are formed and rebalanced 10 weeks after each quarter from the first quarter in 2006 the fourth quarter in 2015. Top is the portfolio consisting of funds with the highest degree of persistency in their AFP score. In panel A we regress each portfolio return on the market factor for the entire time period, panel B for the time period 2006-2008 and panel C for the time period 2009-2015. Standard errors are presented in parenthesis and ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Panel A: 2006-2015		**Panel B: 2006-2008**		**Panel C: 2008-2015**	
VARIABLES	Top	Bottom	Top	Bottom	Top	Bottom
mkt	0.8311***	0.8366***	0.8475***	0.7742***	0.8095***	0.8880***
	(0.0096)	(0.0099)	(0.0154)	(0.0177)	(0.0110)	(0.0118)
Constant	0.0002	0.0001	0.0001	-0.0003	0.0002	0.0002
	(0.0001)	(0.0001)	(0.0003)	(0.0003)	(0.0001)	(0.0002)
Observations	2,311	2,192	685	685	1,689	1,507
R-squared	0.7628	0.7655	0.8159	0.7375	0.7615	0.7903
F-Stat	7425	7150	3027	1919	5385	5672
Prob > F	0	0	0	0	0	0

Table A-6 - Persistent AFP FF3

We form portfolios based on funds' persistency in their AFP score and estimate the Fama & French three-factor time series regression model. The quintile portfolios are formed and rebalanced 10 weeks after each quarter from the first quarter in 2006 the fourth quarter in 2015. Top is the portfolio consisting of funds with the highest degree of persistency in their AFP score. In panel A we regress each portfolio return on the market, value and size factor for the entire time period, panel B for the time period 2006-2008 and panel C for the time period 2009-2015. Standard errors are presented in brackets and ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Panel A: 2006-2015		**Panel B: 2006-2008**		**Panel C: 2008-2015**	
VARIABLES	Top	Bottom	Top	Bottom	Top	Bottom
mkt	0.9770***	1.0009***	0.9628***	1.0179***	0.9432***	1.0034***
	(0.0134)	(0.0135)	(0.0220)	(0.0230)	(0.0153)	(0.0165)
smb	0.3269***	0.3842***	0.2574***	0.5459***	0.3233***	0.2900***
	(0.0214)	(0.0217)	(0.0366)	(0.0381)	(0.0238)	(0.0261)
hml	-0.0158	0.0455**	-0.0950**	-0.1765***	0.0717***	0.0852***
	(0.0215)	(0.0217)	(0.0453)	(0.0471)	(0.0215)	(0.0235)
Constant	0.0000	-0.0001	0.0001	-0.0001	-0.0001	0.0000
	(0.0001)	(0.0001)	(0.0003)	(0.0003)	(0.0001)	(0.0001)
Observations	2,311	2,192	685	685	1,689	1,507
R-squared	0.7845	0.7952	0.8286	0.7988	0.7856	0.8070
F-Stat	2800	2831	1097	901.0	2058	2095
Prob > F	0	0	0	0	0	0

Table A-7 – Persistent AFP Movestay

We form quintile portfolios based on funds' AFP score estimate the Fama & French three-factor time series regression model. The quintile portfolios are formed and rebalanced 10 weeks after each quarter from the first quarter in 2006 the fourth quarter in 2015. Top is the portfolio consisting of funds with the highest degree of persistency in their AFP score. Due to instability in parameters we utilize maximum likelihood estimation in order to estimate endogenous switching regression model using the Movestay command in Stata. We allow for partial correlation between returns and the standard errors are clustered within quarters. Standard errors are presented in brackets and ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively. Regime0 is the between the years 2006-2008 and regime1 is for the years 2009-2015.

Panel A: Persistent AFP Funds

VARIABLES	Top0	Top1	sigma0	sigma1	rho0	rho1
mkt	1.0205***	0.9842***	0.009	0.0063	0.79	-0.06
	(0.0327)	(0.0146)	0.0013	0.0004	0.08	0.03
smb	0.3628***	0.3841***				
	(0.0466)	(0.0298)				
hml	-0.0837	0.0285				
	(0.0513)	(0.0213)				
Constant	0.0084***	0.0001				
	(0.0018)	(0.0002)				

Panel B: Inpersistent AFP Funds

VARIABLES	Bottom0	Bottom1	sigma0	sigma1	rho0	rho1
mkt	1.0757***	0.9886***	0.01	0.005	0.82	-0.43
	(0.0110)	(0.0363)	0.001	0.001	0.03	0.29
smb	0.6443***	0.2644***				
	(0.0688)	(0.0290)				
hml	-0.1680***	0.0815				
	(0.0531)	(0.0509)				
Constant	0.0088***	0.0013				
	(0.0012)	(0.0011)				

Table A-8 - Positive & Negative AFP - CAPM

We form portfolios based on funds' AFP score and estimate the CAPM time series regression model. The funds are divided into two groups depending on whether their AFP is negative or positive. The win and lose portfolios are formed and rebalanced 10 weeks after each quarter from the first quarter in 2006 the fourth quarter in 2015. Win is the portfolio consisting of funds with the positive AFP score and lose consists of the funds with negative AFP scores. In panel A we regress each portfolio return on the market factor for the entire time period, panel B for the time period 2006-2008 and panel C for the time period 2009-2015. Standard errors are presented in brackets and ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Panel A: 2006-2015		**Panel B: 2006-2008**		**Panel C 2009-2015**	
VARIABLES	Positive	Negative	Positive	Negative	Positive	Negative
mkt	0.8087***	0.8312***	0.8411***	0.8232***	0.8095***	0.8363***
	(0.0089)	(0.0089)	(0.0150)	(0.0156)	(0.0110)	(0.0110)
Constant	0.0001	0.0001	-0.0001	-0.0003	0.0002	0.0003*
	(0.0001)	(0.0001)	(0.0003)	(0.0003)	(0.0001)	(0.0001)
Observations	2,374	2,374	685	685	1,689	1,689
R-squared	0.7780	0.7866	0.8209	0.8033	0.7615	0.7740
F-Stat	8312	8745	3131	2790	5385	5778
Prob > F	0	0	0	0	0	0

Table A-9 - Positive & Negative AFP FF3

We form portfolios based on funds' AFP score and estimate the Fama & French three-factor time series regression model. The funds are divided into two groups depending on whether their AFP is negative or positive. The win and lose portfolios are formed and rebalanced 10 weeks after each quarter from the first quarter in 2006 the fourth quarter in 2015. Win is the portfolio consisting of funds with the positive AFP score and lose consists of the funds with negative AFP scores. In panel A we regress each portfolio return on the market, size and value factor for the entire time period, panel B for the time period 2006-2008 and panel C for the time period 2009-2015. Standard errors are presented in brackets and ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Panel A: 2006-2015		**Panel B: 2006-2008**		**Panel C: 2009-2015**	
VARIABLES	Positive	Negative	Positive	Negative	Positive	Negative
mkt	0.9441***	0.9835***	0.9646***	1.0247***	0.9264***	0.9589***
	(0.0124)	(0.0121)	(0.0213)	(0.0206)	(0.0154)	(0.0152)
smb	0.3017***	0.3570***	0.2707***	0.4514***	0.3392***	0.3132***
	(0.0197)	(0.0193)	(0.0354)	(0.0343)	(0.0241)	(0.0238)
hml	-0.0163	0.0512***	-0.1586***	-0.1423***	0.0536**	0.1097***
	(0.0196)	(0.0193)	(0.0438)	(0.0423)	(0.0218)	(0.0215)
Constant	-0.0000	-0.0001	-0.0000	-0.0001	-0.0001	-0.0000
	(0.0001)	(0.0001)	(0.0003)	(0.0002)	(0.0001)	(0.0001)
Observations	2,374	2,374	685	685	1,689	1,689
R-squared	0.7980	0.8140	0.8364	0.8436	0.7711	0.7970
F-Stat	3121	3456	1161	1225	1893	2206
Prob > F	0	0	0	0	0	0

Table A-10 - Positive & Negative Quintiles AFP Movestay

We form portfolios based on funds' AFP score and estimate the Fama & French three-factor time series regression model. The funds are divided into two groups depending on whether their AFP is negative or positive. The win and lose portfolios are formed and rebalanced 10 weeks after each quarter from the first quarter in 2006 the fourth quarter in 2015. Win is the portfolio comprising of funds with the positive AFP score and lose consists of the funds with negative AFP scores. Due to instability in parameters we utilize maximum likelihood estimation in order to estimate endogenous switching regression model using the Movestay command in Stata. We allow for partial correlation between returns and the standard errors are clustered within quarters. Standard errors are presented in brackets and ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively. Regime0 is the between the years 2006-2008 and regime1 is for the years 2009-2015.

Panel A: Funds with Positive AFP

VARIABLES	Positive0	Positive1	sigma0	sigma1	rho0	rho1
mkt	1.0185***	0.9243***	0,0085	0,0012	0,7511	-0,0638
	(0.0090)	(0.0187)	0,0054	0,0006	0,0471	0,0936
smb	0.3618***	0.3356***				
	(0.0211)	(0.0461)				
hml	-0.1464***	0.0529**				
	(0.0387)	(0.0208)				
Constant	0.0075***	0.0001				
	(0.0013)	(0.0004)				

Panel B: Funds with Negative AFP

VARIABLES	Negative0	Negative1	sigma0	sigma1	rho0	rho1
mkt	1.0868***	0.9729***	0,0088	0,0056	0,8230	0,4167
	(0.0063)	(0.0183)	0,0006	0,0005	0,0141	0,2437
smb	0.5573***	0.3367***				
	(0.0305)	(0.0285)				
hml	-0.1273**	0.1140***				
	(0.0495)	(0.0398)				
Constant	0.0084***	-0.0011				
	(0.0008)	(0.0007)				

Table A-11 – AFP FF3 Trend

We form quintile portfolios based on funds' AFP score estimate the Fama & French three-factor time series regression model. The quintile portfolios are formed and rebalanced 10 weeks after each quarter from the first quarter in 2006 the fourth quarter in 2015. Quintile 5 is the portfolio consisting of funds with the highest AFP score. Due to instability in parameters we include a trend variable to capture the cumulative effect of the crisis. In panel A we regress each portfolio return on the market, value and size factor for the entire time period, panel B for the time period 2006-2008 and panel C for the time period 2009-2015. Standard errors are presented in brackets and ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: 2006-2015

VARIABLES	q5	q4	q3	q2	q1	topminusbottom
mkt	0.9679***	0.9683***	0.9686***	0.9174***	0.9521***	0.0158*
	(0.0125)	(0.0129)	(0.0125)	(0.0129)	(0.0125)	(0.0088)
smb	0.3715***	0.2967***	0.2304***	0.2186***	0.3138***	0.0577***
	(0.0199)	(0.0205)	(0.0200)	(0.0205)	(0.0199)	(0.0140)
hml	0.0125	0.0065	0.0320	0.0272	0.0071	0.0054
	(0.0198)	(0.0205)	(0.0199)	(0.0204)	(0.0198)	(0.0139)
trend	0.0000	-0.0000	-0.0000	-0.0000	-0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	-0.0001	-0.0000	0.0000	0.0000	0.0002	-0.0003**
	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Observations	2,374	2,374	2,374	2,374	2,374	2,374
R-squared	0.7965	0.7960	0.8155	0.7895	0.7978	0.0091
F-Stat	2318	2310	2618	2221	2337	5.439
Prob > F	0	0	0	0	0	0.000233

Panel B: 2006-2008

VARIABLES	q5	q4	q3	q2	q1	topminusbottom
mkt	1.0096***	0.9862***	0.9982***	0.9582***	0.9502***	0.0593***
	(0.0222)	(0.0230)	(0.0220)	(0.0238)	(0.0217)	(0.0163)
smb	0.4725***	0.3019***	0.2196***	0.2679***	0.2617***	0.2108***
	(0.0368)	(0.0382)	(0.0366)	(0.0396)	(0.0360)	(0.0271)
hml	-0.1889***	-0.1468***	-0.1529***	-0.1708***	-0.1119**	-0.0770**
	(0.0451)	(0.0468)	(0.0448)	(0.0485)	(0.0442)	(0.0332)
trend	-0.0000	-0.0000	-0.0000	-0.0000	0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Constant	0.0000	0.0002	0.0003	0.0002	0.0001	-0.0000
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0004)
Observations	685	685	685	685	685	685
R-squared	0.8187	0.8213	0.8468	0.8050	0.8312	0.0992
F-Stat	767.7	781.1	939.6	701.7	837.0	18.71
Prob > F	0	0	0	0	0	0

Panel C: 2009-2015

VARIABLES	q5	q4	q3	q2	q1	topminusbottom
mkt	0.9433***	0.9551***	0.9449***	0.8888***	0.9522***	-0.0089
	(0.0153)	(0.0159)	(0.0154)	(0.0154)	(0.0156)	(0.0102)
smb	0.3237***	0.3093***	0.2582***	0.2053***	0.3646***	-0.0409**
	(0.0238)	(0.0248)	(0.0241)	(0.0240)	(0.0244)	(0.0159)
hml	0.0726***	0.0683***	0.1160***	0.1015***	0.0658***	0.0068
	(0.0216)	(0.0225)	(0.0218)	(0.0218)	(0.0221)	(0.0145)
trend	0.0000	0.0000	0.0000	0.0000	-0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	-0.0003	-0.0002	-0.0003	-0.0001	0.0000	-0.0003
	(0.0004)	(0.0005)	(0.0004)	(0.0004)	(0.0005)	(0.0003)
Observations	1,689	1,689	1,689	1,689	1,689	1,689
R-squared	0.7856	0.7788	0.7958	0.7820	0.7752	0.0064
F-Stat	1543	1483	1640	1510	1452	2.731
Prob > F	0	0	0	0	0	0.0278

Table A-12 –Active Share Movestay Trend

We form quintile portfolios based on funds Active Share score and estimate the Fama & French three-factor time series regression model. The quintile portfolios are formed and rebalanced 10 weeks after each quarter from the first quarter in 2006 the fourth quarter in 2015. Quintile 5 is the portfolio consisting of funds with the highest degree of active share. Due to instability in parameters we utilize maximum likelihood estimation in order to estimate endogenous switching regression model using the Movestay command in Stata. In addition to this we include a trend variable to capture the cumulative effect of the crisis. We allow for partial correlation between returns and the standard errors are clustered within quarters. Standard errors are presented in brackets and ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively. Starting with quintile 5 and going downwards in the table, the output for the difference between q5 and q1 is presented at the bottom. Regime0 is the between the years 2006-2008 and regime1 is for the years 2009-2015.

VARIABLES	q50	q51	sigma0	sigma1	rho0	rho1
mkt	0.9470***	0.9073***	0.006	0.004	-0.003	1
	(0.0183)	(0.0125)	0	0	0.492	0
smb	0.6310***	0.5131***				
	(0.0305)	(0.0190)				
hml	-0.1522***	-0.0206				
	(0.0375)	(0.0176)				
trend	-0.0000	0.0000				
	(0.0001)	(0.0000)				
Constant	0.0001	-0.0006				
	(0.0005)	(0.0004)				
VARIABLES	q40	q41	sigma0	sigma1	rho0	rho1
mkt	-1.2299	0.8303***	0.1271	0.0226	0.9889	-1
	(0.0000)	(0.0303)	0.0077	0.001	0.00159	0
smb	0.1732	-0.0205				
	(0.0000)	(0.0000)				
hml	0.4826	-0.1212				
	(0.8416)	(0.1031)				
trend	0.0042***	-0.0003***				
	(0.0006)	(0.0001)				
Constant	0.0780***	0.0218***				
	(0.0069)	(0.0021)				
VARIABLES	q30	q31	sigma0	sigma1	rho0	rho1
mkt	0.9418***	0.9321***	0.0056	0.0044	0.0591	0.999
	(0.0185)	(0.0131)	0.0002	0	0.5851	0
smb	0.2191***	0.2004***				
	(0.0307)	(0.0200)				
hml	-0.1435***	0.0313*				
	(0.0378)	(0.0185)				
trend	-0.0001	0.0000				
	(0.0001)	(0.0000)				
Constant	0.0002	-0.0005				
	(0.0005)	(0.0004)				
VARIABLES	q20	q21	sigma0	sigma1	rho0	rho1
mkt	0.9426***	0.9654***	0.0002	0.0050	0.0030	1
	(0.0213)	(0.0152)	0.0062	0	0.5072	0
smb	0.2121***	0.2275***				
	(0.0355)	(0.0232)				
hml	-0.1261***	0.0520**				
	(0.0437)	(0.0214)				
trend	-0.0000	0.0000				
	(0.0001)	(0.0000)				
Constant	0.0002	-0.0005				
	(0.0005)	(0.0005)				
VARIABLES	q10	q11	sigma0	sigma1	rho0	rho1
mkt	0.9404***	0.9515***	0.0056	0.0042	0.001423	1
	(0.0183)	(0.0127)	0.002	0	0.513	0
smb	0.1736***	0.1933***				
	(0.0304)	(0.0193)				
hml	-0.1071***	0.0474***				
	(0.0374)	(0.0178)				
trend	-0.0000	0.0000				
	(0.0001)	(0.0000)				
Constant	0.0002	-0.0007*				
	(0.0005)	(0.0004)				
VARIABLES	topminusbottom0	topminusbottom1	sigma0	sigma1	rho0	rho1
mkt	0.0066	-0.0439***	0.004	0.0030	-0.0035	-1
	(0.0132)	(0.0091)	0.0001	0,0000	0.711	0,0000
smb	0.4574***	0.3200***				
	(0.0219)	(0.0139)				
hml	-0.0450*	-0.0661***				
	(0.0269)	(0.0129)				
trend	-0.0000	-0.0000				
	(0.0000)	(0.0000)				
Constant	-0.0001	0.0001				
	(0.0003)	(0.0003)				

Descriptive Statistics Appendix

Table A-13: CAR Based on FF3 Alphas

Total nr of observations	9 852
Cross-sectional average CAR	-0.57%
Cross-sectional standard deviation of CAR	7.93%
Cross-sectional maximum CAR	143.38%
Cross-sectional minimum CAR	-86.50%
99th pct	20.28%
90th pct	7.94%
75th pct	3.22%
Median	-0.46%
25th pct	-4.37%
10th pct	-8.93%
1st pct	-21.83%
Nr. obs > 100 %	2
Nr. obs > 50 %	4
Nr. obs > 25 %	43
Nr. obs > 10 %	620
Nr. obs > 5 %	1 777
Nr. obs > 2.5 %	2 803
Nr. obs < -2.5 %	3 534
Nr. obs < -5 %	2 157
Nr. obs < -10 %	800
Nr. obs < -25 %	61
Nr. obs < -50 %	8
Nr. obs < -100 %	0
Nr. obs > |10 %|	1 420
Nr. obs > |5 %|	3 934
Nr. obs > |2.5 %|	6 337
Nr. obs within 1 std dev (-7.93 % to 7.92 %)	7 672
	77.9%
Nr. obs within 2 std dev (-15.85 % to 15.84 %)	9 386
	95.3%

Table A-14: Most Volatile around Earnings

Stocks up more than 50 %	Earnings Ann. Date	Cum. Return (BBG)	Checked	CAR w/ FF3 alphas
Stockwik Forvaltning AB	2015-02-11	145.11%	√	143.4%
ACAP Invest AB	2013-10-24	141.91%	√	141.9%
Eniro AB	2009-04-27	55.67%	√	55.9%
Hemtex AB	2014-02-11	53.24%	√	53.1%
Stocks down more than 50 %				
D Carnegie & Co AB/Old	2008-10-24	-87.23%	√	-86.5%
A-Com AB	2012-11-23	-68.58%	√	-67.2%
XANO Industri AB	2014-05-08	-57.59%	√	-61.9%
Teligent AB	2008-02-12	-56.15%	√	-57.5%
Nordic Service Partners Holding	2008-11-10	-53.05%	√	-54.9%
Eniro AB	2010-10-28	-49.62%	√	-54.5%
PA Resources AB	2012-11-07	-45.26%	√	-52.0%
Fingerprint Cards AB	2012-07-10	-49.96%	√	-50.5%

Table A-15: AFP Based on CAPM CARs

Nr. obs	1 423
Avg. funds over the 39 quarters	36.5
Cross-Sectional Mean	0.0012
Cross-Sectional Standard Deviation	0.0118
Cross-Sectional Maximum	0.0483
Cross-Sectional Minimum	-0.0635
99th pct	0.0346
90th pct	0.0163
75th pct	0.0073
Median	0.0005
25th pct	-0.0064
10th pct	-0.0121
1st pct	-0.0252
Nr. obs within 1 std dev (-0.0106 to 0.01297)	1 030
	72.4%
Nr. obs within 2 std devs (-0.0224 to 0.02478)	1 357
	95.4%

Figure A-1 - Persistence of Active Share Quintiles

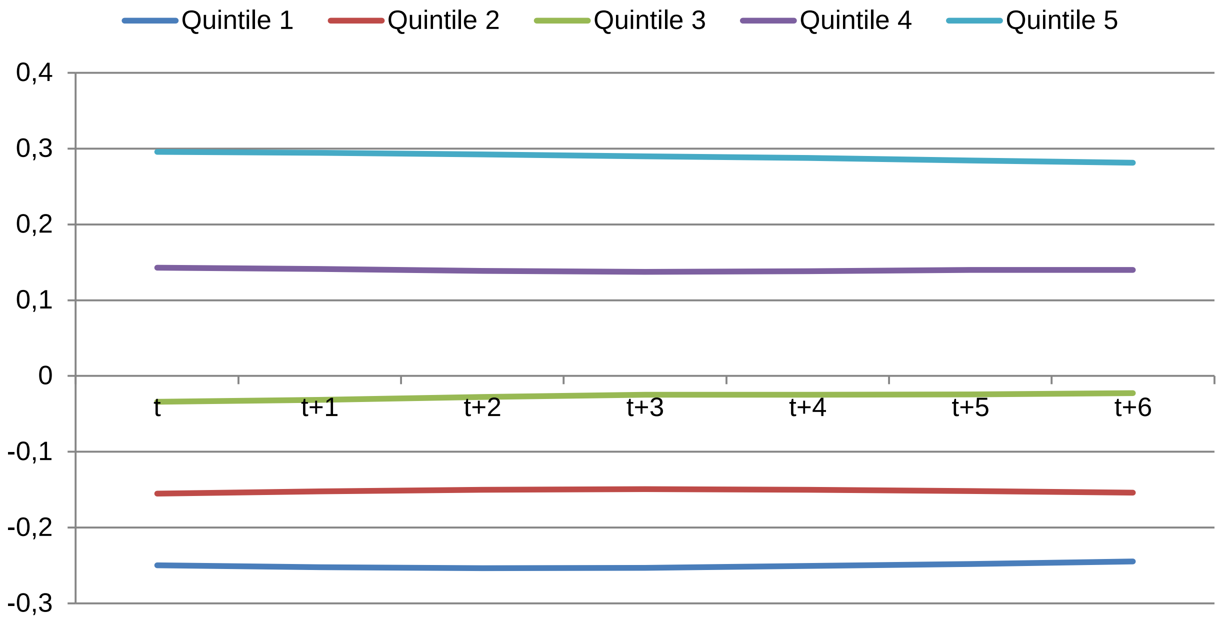
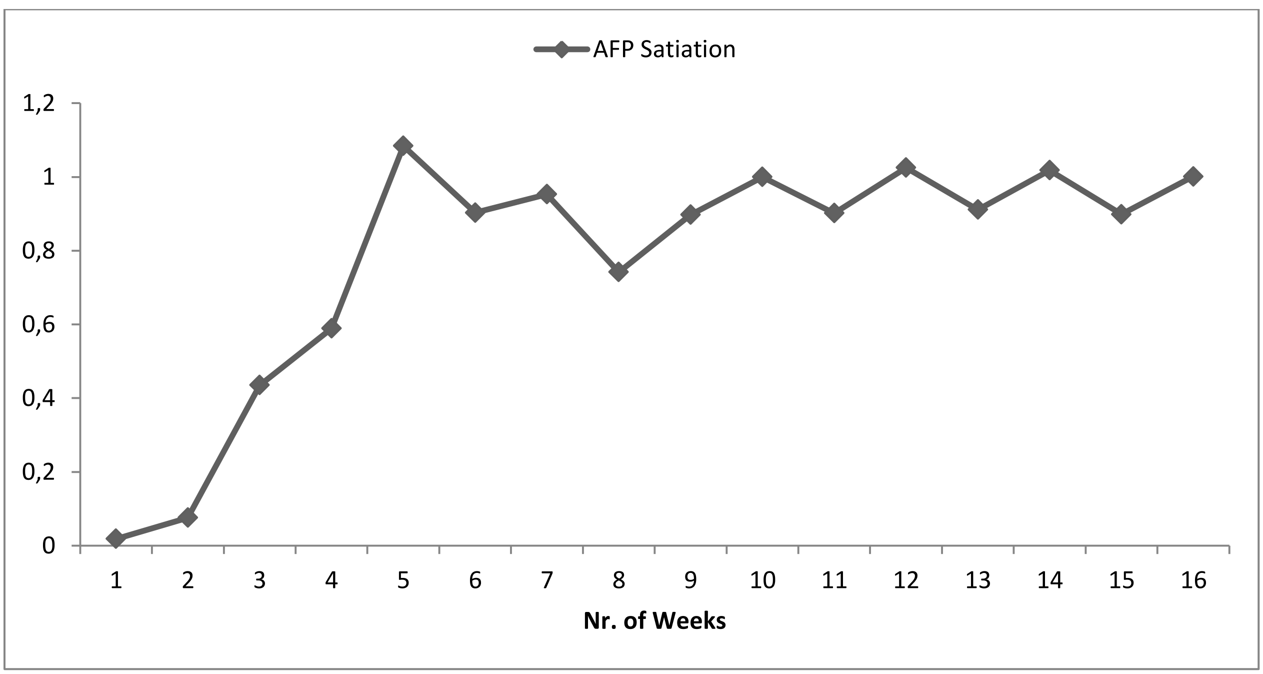


Figure A-2 - Stabilization of AFP after 10 weeks



MatLab Code Appendix

Fama-French Three Factor Estimation

```
clear all
load quarter_dates.mat; SMB_fulltime = 0; HML_fulltime = 0; dates_fulltime = 0;
for t = 1:41
% Shares Outstanding & Portfolio 1-6
[~, ~, raw0_0] = xlsread('SAX FF values.xlsm',t,'D1:D320'); [~, ~, raw0_1] = xlsread('SAX FF values.xlsm',t,'K1:K320');
raw = [raw0_0,raw0_1]; raw(cellfun(@(x) ~isempty(x) && isnumeric(x) && isnan(x),raw)) = {''};
R = cellfun(@(x) ~isnumeric(x) && ~islogical(x),raw); raw(R) = {NaN}; data = reshape([raw{:}],size(raw));
Shares = data(:,1); FF_port = data(:,2); clearvars data raw raw0_0 raw0_1 R;

I_1 = zeros(size(FF_port,1),1); I_2 = zeros(size(FF_port,1),1); I_3 = zeros(size(FF_port,1),1);
I_4 = zeros(size(FF_port,1),1); I_5 = zeros(size(FF_port,1),1); I_6 = zeros(size(FF_port,1),1);
for i = 1:size(FF_port,1)
    if FF_port(i,1) == 1
        I_1(i,1) = 1;end
    if FF_port(i,1) == 2
        I_2(i,1) = 1;end
    if FF_port(i,1) == 3
        I_3(i,1) = 1;end
    if FF_port(i,1) == 4
        I_4(i,1) = 1;end
    if FF_port(i,1) == 5
        I_5(i,1) = 1;end
    if FF_port(i,1) == 6
        I_6(i,1) = 1;end
end
I_1 = Shares.*I_1; I_2 = Shares.*I_2; I_3 = Shares.*I_3; I_4 = Shares.*I_4; I_5 = Shares.*I_5; I_6 = Shares.*I_6;
I_1 = I_1(3:end,1); I_2 = I_2(3:end,1); I_3 = I_3(3:end,1); I_4 = I_4(3:end,1); I_5 = I_5(3:end,1); I_6 = I_6(3:end,1);
% Prices
[~, ~, raw, dates] = xlsread('stock_returns_allquarters_fulltime.xlsm',t,'A3:A207','',@convertSpreadsheetExcelDates);
raw(cellfun(@(x) ~isempty(x) && isnumeric(x) && isnan(x),raw)) = {''};
dates = dates(:,1); R = cellfun(@(x) ~isnumeric(x) && ~islogical(x),raw);
raw(R) = {NaN}; R = cellfun(@(x) ~isnumeric(x) && ~islogical(x),dates);
dates(R) = {NaN}; dates = datetime([dates{:,1}].', 'ConvertFrom', 'Excel');
dates = datenum(dates); dates = m2xdate(dates); dates = dates(3:end,:); clearvars raw R;
[~, ~, raw] = xlsread('stock_returns_allquarters_fulltime.xlsm',t,'B3:ML207');
raw(cellfun(@(x) ~isempty(x) && isnumeric(x) && isnan(x),raw)) = {''};
R = cellfun(@(x) ~isnumeric(x) && ~islogical(x),raw);
raw(R) = {NaN}; stock_p = reshape([raw{:}],size(raw)); clearvars raw R;

stock_p(isnan(stock_p) == 1) = 0; liquid = (sum(stock_p==0)<90).*(1:1:size(stock_p,2));
for p = 1:5
for n = 1:size(stock_p,2)
    if liquid(1,n) == 0
        continue
    end
    for o = 1:121
        if stock_p(o,n) == 0
            if o == 1
               stock_p(o,n) = stock_p(o+p,n);
            else
                if o == 121
                    stock_p(o,n) = stock_p(o-p,n);
                else
                stock_p(o,n) = (stock_p(o-1,n)+stock_p(o+1,n))/nnz([stock_p(o-1,n),stock_p(o+1,n)]);
                end
            end
            end
        end
end
end
stock_p(stock_p == 0) = NaN; I = ind2sub(size(dates),find(dates==quarter_dates(t,1)));
stock_p = stock_p(I+2:end,1:size(I_1,1)); stock_r = price2ret(stock_p,[],'Periodic'); stock_r(isnan(stock_r)==1) = 0;
I_1 = I_1'; I_1 = repmat(I_1,size(stock_p,1),1); I_2 = I_2'; I_2 = repmat(I_2,size(stock_p,1),1);
I_3 = I_3'; I_3 = repmat(I_3,size(stock_p,1),1); I_4 = I_4'; I_4 = repmat(I_4,size(stock_p,1),1);
I_5 = I_5'; I_5 = repmat(I_5,size(stock_p,1),1); I_6 = I_6'; I_6 = repmat(I_6,size(stock_p,1),1);

MC_1=I_1.*stock_p; sum_MC_1=repmat(nansum(MC_1,2),1,size(stock_p,2)); W_1=MC_1./sum_MC_1; W_1=W_1(2:end,:); W_1(isnan(W_1)==1)
MC_2=I_2.*stock_p; sum_MC_2=repmat(nansum(MC_2,2),1,size(stock_p,2)); W_2=MC_2./sum_MC_2; W_2=W_2(2:end,:); W_2(isnan(W_2)==1)
MC_3=I_3.*stock_p; sum_MC_3=repmat(nansum(MC_3,2),1,size(stock_p,2)); W_3=MC_3./sum_MC_3; W_3=W_3(2:end,:); W_3(isnan(W_3)==1)
MC_4=I_4.*stock_p; sum_MC_4=repmat(nansum(MC_4,2),1,size(stock_p,2)); W_4=MC_4./sum_MC_4; W_4=W_4(2:end,:); W_4(isnan(W_4)==1)
MC_5=I_5.*stock_p; sum_MC_5=repmat(nansum(MC_5,2),1,size(stock_p,2)); W_5=MC_5./sum_MC_5; W_5=W_5(2:end,:); W_5(isnan(W_5)==1)
MC_6=I_6.*stock_p; sum_MC_6=repmat(nansum(MC_6,2),1,size(stock_p,2)); W_6=MC_6./sum_MC_6; W_6=W_6(2:end,:); W_6(isnan(W_6)==1)

for n=1:size(W_1,1)
    w1=W_1(n,:)'; w2=W_2(n,:)'; w3=W_3(n,:)'; w4=W_4(n,:)'; w5=W_5(n,:)'; w6=W_6(n,:)';
    FF1(n,1)=stock_r(n,:)*w1; FF2(n,1)=stock_r(n,:)*w2; FF3(n,1)=stock_r(n,:)*w3; ...
    FF4(n,1)=stock_r(n,:)*w4; FF5(n,1)=stock_r(n,:)*w5; FF6(n,1)=stock_r(n,:)*w6;
end

SMB = ((1/3)*FF1+(1/3)*FF2+(1/3)*FF3) - ((1/3)*FF4+(1/3)*FF5+(1/3)*FF6);
HML = ((1/2)*FF1+(1/2)*FF4) - ((1/2)*FF3+(1/2)*FF6); Q_dates = dates(I+1:end,1);

xlswrite('hemmagjorda_factors.xlsm',Q_dates,t,'a1'); xlswrite('hemmagjorda_factors.xlsm',SMB,t,'b1'); xlswrite('hemmagjorda_fa

SMB_fulltime = vertcat(SMB_fulltime,SMB); HML_fulltime = vertcat(HML_fulltime,HML); dates_fulltime = vertcat(dates_fulltime,Q_

clearvars Shares FF_port SMB HML stock_p stock_r Q_dates dates liquid FF1 FF2 FF3 FF4 FF5 FF6 I_1 I_2 I_3 I_4 I_5 I_6 ...
    MC_1 MC_2 MC_3 MC_4 MC_5 MC_6 sum_MC_1 sum_MC_2 sum_MC_3 sum_MC_4 sum_MC_5 sum_MC_6 W_1 W_2 W_3 W_4 W_5 W_6
t
end
SMB_fulltime = SMB_fulltime(2:end); HML_fulltime = HML_fulltime(2:end); dates_fulltime = dates_fulltime(2:end);
SMB_fulltime(SMB_fulltime==0)=NaN; HML_fulltime(HML_fulltime==0)=NaN;
xlswrite('Currency factors - SAX MKT.xlsx',SMB_fulltime,1,'c2'); xlswrite('Currency factors - SAX MKT.xlsx',HML_fulltime,1,'d2
xlswrite('Currency factors - SAX MKT.xlsx',dates fulltime,1,'f2');
```

Cumulative Abnormal Return (CAR) Calculation

```
[~, ~, raw, dates] = xlsread('Currency factors - SAX MKT.xlsx','Values','','',@convertSpreadsheetExcelDates);
raw(cellfun(@(x) ~isempty(x) && isnumeric(x) && isnan(x),raw)) = {''}; raw = raw(:,[2,3,4,5,6]); dates = dates(:,1);
R = cellfun(@(x) ~isnumeric(x) && ~islogical(x),raw); raw(R) = {NaN};
R = cellfun(@(x) ~isnumeric(x) && ~islogical(x),dates); dates(R) = {NaN};
data = reshape([raw{:}],size(raw)); all_factor_dates = datetime([dates{:,1}].', 'ConvertFrom', 'Excel');
MKT = data(:,1); SMB = data(:,2); HML = data(:,3); RF = data(:,4); RM_RF = MKT-RF;

FF3 = horzcat(ones(size(MKT)),RM_RF,SMB,HML); all_factor_dates=datenum(all_factor_dates);
clearvars data raw dates R;
%%
CAR = zeros(320,39); T=39;
for t = 1:T
[~, ~, raw, dates] = xlsread('SAX_index_1beta_10w_values_lite.xlsm',t,'I3:I350','',@convertSpreadsheetExcelDates);
raw(cellfun(@(x) ~isempty(x) && isnumeric(x) && isnan(x),raw)) = {''}; dates = dates(:,1);
R = cellfun(@(x) ~isnumeric(x) && ~islogical(x),raw); raw(R) = {NaN};
R = cellfun(@(x) ~isnumeric(x) && ~islogical(x),dates); dates(R) = {NaN};
earn_ann_dt = datetime([dates{:,1}].', 'ConvertFrom', 'Excel'); earn_ann_dt = datenum(earn_ann_dt);
clearvars raw dates R;

[~, ~, raw] = xlsread('SAX_index_1beta_10w_values_lite.xlsm',t,'A3:A350');
raw(cellfun(@(x) ~isempty(x) && isnumeric(x) && isnan(x),raw)) = {''};index_members = raw(:,1);

[~, ~, raw] = xlsread('SAX_index_1beta_10w_values_lite.xlsm',t,'D3:D350');
raw(cellfun(@(x) ~isempty(x) && isnumeric(x) && isnan(x),raw)) = {''}; R = cellfun(@(x) ~isnumeric(x) && ~islogical(x),raw);
raw(R) = {NaN}; weight = reshape([raw{:}],size(raw)); weight = weight';
clearvars raw R;

[~, ~, raw] = xlsread('stock_returns_allquarters.xlsm',t,'B3:ML192');
raw(cellfun(@(x) ~isempty(x) && isnumeric(x) && isnan(x),raw)) = {''}; R = cellfun(@(x) ~isnumeric(x) && ~islogical(x),raw);
raw(R) = {NaN}; stock_ret = reshape([raw{:}],size(raw));
clearvars raw R;

[~, ~, raw] = xlsread('stock_returns_allquarters.xlsm',t,'A4:A192');
raw(cellfun(@(x) ~isempty(x) && isnumeric(x) && isnan(x),raw)) = {''};
R = cellfun(@(x) ~isnumeric(x) && ~islogical(x),raw); raw(R) = {NaN};
factor_dates = reshape([raw{:}],size(raw)); factor_dates = x2mdate(factor_dates);
clearvars raw R;

    for m = 1:size(index_members)
        loop_dt = earn_ann_dt(m,1);
        if isnan(loop_dt)==1
            continue
        end
        M = ind2sub(size(factor_dates),find(factor_dates == loop_dt));
        while isempty(M) == 1
            loop_dt = loop_dt-1;
            M = ind2sub(size(factor_dates),find(factor_dates == loop_dt));
        end
        reg_data(:,m) = stock_ret(M-121:M-1,m);
    end

reg_data(isnan(reg_data) == 1) = 0;
liquid = (sum(reg_data==0)<90).*(1:1:size(reg_data,2));

for p = 1:3
for n = 1:size(reg_data,2)
    if liquid(1,n) == 0
        continue
    end
    for o = 1:121
        if reg_data(o,n) == 0
            if o == 1
               reg_data(o,n) = reg_data(o+p,n);
            else
                if o == 121
                    reg_data(o,n) = reg_data(o-p,n);
                else
                reg_data(o,n) = (reg_data(o-1,n)+reg_data(o+1,n))/nnz([reg_data(o-1,n),reg_data(o+1,n)]);
                end
            end
            end
        end
end
end

reg_data(reg_data == 0) = NaN;
reg_rets = price2ret(reg_data);

for a = 1:size(index_members)
        loop_dt = earn_ann_dt(a,1);
        if isnan(loop_dt)==1
            continue
        end
        A = ind2sub(size(all_factor_dates),find(all_factor_dates == loop_dt));
        while isempty(A) == 1
            loop_dt = loop_dt-1;
            A = ind2sub(size(all_factor_dates),find(all_factor_dates == loop_dt));
        end
reg_rets(:,a) = reg_rets(:,a) - RF(A-121:A-2);
[b] = regress(reg_rets(:,a),FF3(A-121:A-2,:));
coeffs(a,:,t) = b(2:4)';
end
```

CAR continued

```
    for m = 1:size(index_members)
        loop_dt = earn_ann_dt(m,1);
        if isnan(loop_dt)==1
            continue
        end
        M = ind2sub(size(factor_dates),find(factor_dates == loop_dt));
        while isempty(M) == 1
            loop_dt = loop_dt-1;
            M = ind2sub(size(factor_dates),find(factor_dates == loop_dt));
        end
        if M == 190
            window_data(:,m) = [stock_ret(M-1:M,m);0;0];
        else
            if M == 189
                window_data(:,m) = [stock_ret(M-1:M+1,m);0];
            else
        window_data(:,m) = stock_ret(M-1:M+2,m);
            end
        end

        window_RM_RF = RM_RF(M+1:M+3,1); window_SMB = SMB(M+1:M+3,1); window_HML = HML(M+1:M+3,1);
        window_factor_rets(:,:,m) = horzcat(window_RM_RF,window_SMB,window_HML);
    end
window_data(isnan(window_data) == 1) = 0;
window_liquid = (sum(window_data==0)<1).*(1:1:size(window_data,2));

for p = 1:3
for n = 1:size(window_data,2)
    if window_liquid(1,n) == 0
        continue
    end
    for o = 1:3
        if window_data(o,n) == 0
            if o == 1
               window_data(o,n) = window_data(o+p,n);
            else
                if o == 120
                    window_data(o,n) = window_data(o-p,n);
                else
                window_data(o,n) = (window_data(o-1,n)+window_data(o+1,n))/nnz([window_data(o-1,n),window_data(o+1,n)]);
                end
            end
            end
        end
end
end
window_data(window_data == 0) = NaN; window_rets = price2ret(window_data);

for m = 1:size(window_factor_rets,3)
AR(:,m) = window_rets(:,m) - window_factor_rets(:,1,m)*coeffs(m,1,t) - window_factor_rets(:,2,m)*coeffs(m,2,t) ...
    - window_factor_rets(:,3,m)*coeffs(m,3,t);
end
CAR(1:size(AR,2),t) = nansum(AR)';
clearvars reg_data earn_ann_dt index_members AR window_data window_factor_rets reg_rets ...
    coeffs liquid window_liquid window_rets
t
end
%%
save('CAR_FF3SAX_10w.mat','CAR') % Change if change
%%
CAR(CAR==0)=NaN;
for t = 1:T
    CAR_t = CAR(:,t);
    xlswrite('SAX_index_FF3SAX_10w.xlsm',CAR_t,t,'W3') % Change if change
end
```

AFP Calculation & Quintile Portfolio Construction

```
Q = 39; s = 1; fund_diffs = zeros(49,Q); summary_AFP = zeros(49,Q); summary_AFP_inst = zeros(49,Q); nr_holdings = zeros(49,Q);
sum_diffs_amount_t = zeros(49,Q); sum_diffs_inst_t = zeros(49,Q); nr_holdings_universe = zeros(49,Q);

load('Input/SAX 3FF/SAX_index_CAPMSAX_10w.mat'); % Change for change
load('Input/SAX_funds.mat'); load('Input/data_fund_age.mat');

[~, ~, raw] = xlsread('Input/SAX 3FF/10weeks_indexlist.xlsx','Sheet1','B1:B40');
rebal_list = reshape([raw{:}],size(raw)); clearvars raw;

data = xlsread('Input/fund_sheet_index.xlsx',1); sheet_inst_nr = data(:,1); sheet_nr = data(:,2); clearvars data raw;
for t = 1:Q
FI_data = [ 'Input/FI/FI_Q' num2str(t) '.mat' ]; load(FI_data);
index_isin=ind_isin(:,:,t); index_tkr=ind_tkr(:,:,t); index_car=ind_car(:,:,t); index_w=ind_w(:,:,t);
%% Filter out only chosen funds' holdings etc.
chosen_isin = cell(1,1); chosen_inst = zeros(1,1); chosen_mkt_cap = zeros(1,1);
for i=1:size(select_inst_list)
    K(i,1) = ind2sub(size(sheet_inst_nr),find(sheet_inst_nr == select_inst_list(i,1)));
    if fund_age((rebal_list(s)),K(i,1)) == 0
        continue
    else
    I=ind2sub(size(inst_nr),find(inst_nr == select_inst_list(i,1)));
    loop_inst = inst_nr(I); loop_isin = isin(I); loop_mkt_cap = mkt_cap(I);

    chosen_isin = vertcat(chosen_isin, loop_isin); chosen_inst = vertcat(chosen_inst, loop_inst);
    chosen_mkt_cap = vertcat(chosen_mkt_cap, loop_mkt_cap);
    end
end
I = ismember(select_inst_list,chosen_inst);
active_inst_list = I.*select_inst_list; active_inst_list(any(active_inst_list==0,2),:)=[];
%% Calculate AFP for each fund current quarter
sum_diff = zeros(size(active_inst_list));
for i=1:size(active_inst_list)

    I=ind2sub(size(chosen_inst),find(chosen_inst == active_inst_list(i,1)));
    fund_isins =  chosen_isin(I); fund_mkt_caps = chosen_mkt_cap(I);
    fund_w = fund_mkt_caps./sum(fund_mkt_caps); nr_holdings(i,t) = nnz(fund_w);

    for k = 1:size(fund_isins)
        loop_isin = fund_isins(k,1);
        loop_isin = char(loop_isin);

        isin_match = strfind(index_isin,loop_isin);
        isin_match = find(~cellfun(@isempty,isin_match));

        if isin_match > 0;
           isin_index(k,1) = isin_match;
        end
    end
fund_ind_pos = zeros(size(index_w));
    for l=1:size(isin_index)
        if isin_index(l,1) == 0;
        continue
        end
        fund_ind_pos(isin_index(l,1),1) = fund_ind_pos(isin_index(l,1),1)+fund_w(l,1);
    end
    diff = fund_ind_pos - index_w; AFP(i,1) = index_car'*diff;
    clearvars fund_isins fund_mkt_caps fund_w isin_match isin_index fund_ind_pos diff
end
inst_sum_diff = horzcat(active_inst_list,sum_diff); inst_sum_diff_sorted = sortrows(inst_sum_diff,2);
sum_diffs_inst_t(1:size(inst_sum_diff,1),t) = inst_sum_diff_sorted(:,1);
sum_diffs_amount_t(1:size(inst_sum_diff,1),t) = inst_sum_diff_sorted(:,2);

funds_AFP = horzcat(active_inst_list,AFP);
clearvars chosen_inst chosen_isin chosen_mkt_cap index_isin index_tkr index_w ...
    sum_diff inst_sum_diff inst_sum_diff_sorted index_car
funds_AFP_sorted = sortrows(funds_AFP,2);
summary_AFP(1:size(funds_AFP_sorted,1),t) = funds_AFP_sorted(:,2);
summary_AFP_inst(1:size(funds_AFP_sorted,1),t) = funds_AFP_sorted(:,1);

%% Form fund decile portfolios
n = (size(active_inst_list,1)/5);
n2=n+n; n3=n2+n; n4=n3+n;
N1=round(n); N2=round(n2); N3=round(n3); N4=round(n4);

port_1 = funds_AFP_sorted(1:N1,1); port_2 = funds_AFP_sorted(N1+1:N2,1); port_3 = funds_AFP_sorted(N2+1:N3,1);
port_4 = funds_AFP_sorted(N3+1:N4,1); port_5 = funds_AFP_sorted(N4+1:end,1);

port_1_afp = funds_AFP_sorted(1:N1,2); port_2_afp = funds_AFP_sorted(N1+1:N2,2); port_3_afp = funds_AFP_sorted(N2+1:N3,2);
port_4_afp = funds_AFP_sorted(N3+1:N4,2); port_5_afp = funds_AFP_sorted(N4+1:end,2);

dec_ports_data = [ 'Quintile Portfolios/CAPMSAX_10w_Q' num2str(t) '.mat' ]; % Change for change
save(dec_ports_data, 'port_1','port_2','port_3','port_4','port_5',...
'port_1_afp','port_2_afp','port_3_afp','port_4_afp','port_5_afp')

clearvars active_inst_list AFP funds_AFP_sorted funds_AFP port_1 port_2 port_3 port_4 port_5 ...
port_1_afp port_2_afp port_3_afp port_4_afp port_5_afp n n2 n3 n4

s = s+1; t
end
save('Output results/all_AFP_10w_CAPMSAX.mat','summary_AFP','summary_AFP_inst') % Change for change
```

Quintile Portfolio Returns Calculation

```
data = xlsread('Input/fund_sheet_index.xlsx',1); inst_nr = data(:,1); sheet_nr = data(:,2); clearvars data raw;

load('Input/SAX 3FF/data_new_fund_returns.mat');

[~, ~, raw] = xlsread('Input/SAX 3FF/10weeks_indexlist.xlsx','Sheet1','B1:B40');
index_list = reshape([raw{:}],size(raw)); clearvars raw;

s = 1; Q = 39; ps = 5; daily_returns = zeros(1,ps);

for t = 1:Q
    dec_ports_data = ['Quintile Portfolios/FF3SAX_10w_Q' num2str(t) '.mat' ]; % Change for change
    load(dec_ports_data);
    port1 = zeros(size(port_1,1)+2,1); port1(1:size(port_1),1) = port_1;
    port2 = zeros(size(port_1,1)+2,1); port2(1:size(port_2),1) = port_2;
    port3 = zeros(size(port_1,1)+2,1); port3(1:size(port_3),1) = port_3;
    port4 = zeros(size(port_1,1)+2,1); port4(1:size(port_4),1) = port_4;
    port5 = zeros(size(port_1,1)+2,1); port5(1:size(port_5),1) = port_5;

    k = 1;
    for p = [port1 port2 port3 port4 port5]
        j = 1;
        for i = 1:size(p,1)
            I = ind2sub(size(inst_nr),find(inst_nr == p(i,1)));
            if isempty(I) == 1
                continue
            else
            loop_cols(:,j) = sheet_nr(I);
            port_return(:,j) = new_fund_returns((index_list(s)):index_list(s+1)-1,loop_cols(1,j));
            j = j+1;
            end
        clearvars loop_cols
        end

        w(1:size(port_return,2),1) = 1./size(port_return,2);
        dec_return(:,k) = port_return*w;
        k = k+1; clearvars port_return w
    end
        s = s+1;
        daily_returns = vertcat(daily_returns,dec_return);
        clearvars port_return w dec_return
end
daily_returns(daily_returns==0)=NaN;
xlswrite('Output results/daily_returns_FF3SAX_10w_quintiles.xlsx',daily_returns,1); % Change for change
```