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- Mutual Fund Performance in the U.S. Market -

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Abstract

This paper examines whether actively managed U.S. mutual equity funds exhibit any statistical persistence in mutual fund performance by applying three different methods. The backbone for the methods is the sorting procedure that creates ten equally weighted portfolios based on lagged one-year simple returns of the mutual funds and rank them accordingly from best to worst. The ranked portfolios are further implemented in three different holding strategies; they rebalance every three, six and twelve months. The first method obtains risk-adjusted returns and alphas from all ten portfolios by practicing CAPM, Carhart 4-factor and Fama and French 5-factor model. The alphas serve as the main risk-adjusted measure of performance. Sharpe ratio is also presented as an external measure of performance for comparative purposes. Second method investigates market timing ability of all portfolios by following Henriksson and Merton procedures of detecting such feat. The third method tests for rank dependency by constructing contingency tables. The findings mostly favor no persistence in mutual fund performance as the ranked portfolios were not able to generate significant positive risk-adjusted alphas, but two of them obtained the opposite, significant negative alphas in all three holding strategies. No market timing ability was revealed in any of the ranked portfolios. However, Contingency tables were able to capture persistent behavior in portfolio rankings as these rankings together with holding periods appear to influence the excess returns.

Acknowledgements

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Wan Hin Hui & Tommy Fjetland
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Introduction

The financial markets are growing and ever-evolving by experiencing periods of catastrophic setbacks and prosperities in the global economy. Different types of asset classes and securities have emerged and/or gained popularity during the past century, and among them is the famously known mutual fund. The recent global financial crisis of 2008 is considered as the biggest pitfall since The Great Depression, where it has undisputedly changed how the financial markets behave and operate today. In these volatile periods, uncertainty tends to alter the risk appetite and tolerance of private and institutional investors. Naturally, the majority will reallocate their holdings to less risk-exposed assets and wait until the state of the economy stabilizes. As markets collapse, key policy rates tend to be lowered as a result of governments attempting to innervate and boost economies in recessions. Depending on the level of aggression, the low rate may produce undesirable real rate of return on low risk investments type such as saving accounts, resulting well-diversified mutual funds to become more appealing and profitable over time.

We often come across news about active fund managers that achieves returns far above its corresponding benchmark; for instance, Fidelity Select Biotechnology Portfolio's (Money.US.News 2015) 3-year total return was 29.75% (09.30.2015) whereas its benchmark, S&P 1500 Health Care only produced a return of 11.87%. This is only one example, after more thorough research, we can find large amount of mutual funds that have generated higher returns for their investors than what the benchmark could have accomplished. It appears to be growing a strong acceptance globally that mutual funds, in general, realize higher returns than traditional saving accounts. The higher returns have possibly become the most frequent used argument in mutual fund industry when marketing their products. Such marketing strategies have been condemned countless by academics. In financial theory, there is no such thing as "free lunch", i.e. one cannot achieve higher expected returns by simply change their assets allocation without increasing the level of risk (assuming no mispricing). Higher returns relative to similar asset or benchmark must be a result of significantly higher risk. Hence, whether actively managed funds can consistently outperform passive funds or indices in terms of risks associated to their portfolios become questionable. Arguably, non-professional investors have "chasing returns" behavior, thus it is important to distinguish between skill and luck of the managers' performance such that investors with limited financial knowledge are not fooled by the historical gross return of the portfolio. Another important feature is the fees charged by the fund managers, as it may eliminate all potential superior returns. Academics have therefore found methods to obtain risk-adjusted returns, such that an asset must generate higher returns comparative to the risk it holds in order to be justified. Several researchers have examined the capability of mutual funds to produce abnormal returns, for example Jensen (1968) Fama and French (2010) and Carhart (1997). The findings have mostly been shattering for the fund managers. Barely any funds were able to produce better returns than the risk-adjusted model would predict. Despite the evidences presented, mutual fund industry is still using raw (unadjusted) returns as their core marketing strategy when introducing funds to the public.

This strategy comprises other implications, which will also be the key subject of our thesis. The instinctively pleasing thought that high past returns will result to high future returns is dubious in the perspective of finance literature. This form of mentality is equivalent to momentum strategies, as they believe past returns are predictors of future returns, characterized as persistence in returns. Naturally, the academic world has investigated this matter, e.g. Malkiel (1995) and Carhart (1997). The findings are slightly mixed, but the general consensus is that hardly any possess persistent behavior in the risk-adjusted world. In one of the latest paper describing short-term persistence, Bollen and Busse (2005) found statistical significance in the top decile of all portfolios (10) and the rest being either insignificant or significant in underperformance.

In this thesis, we address the issue of persistence in mutual fund performance by following a methodology similar to the ones applied in Carhart (1997) and Bollen and Busse (2005), and implement those in a slight different manner. The overall goal is to test whether active managed funds are able to generate superior returns in the last decades; the time period from 2000 to 2015 and compare the results with earlier findings to see if there are significant changes in terms of risk-adjusted measure of performance reflected by their alphas in different time horizons.

The foundation of our analysis is defining three different trading strategies. First step involves ranking the funds to their lagged one-year simple returns, also commonly referred as one-year moving average and further formed into ten equally weighted portfolios from highest to lowest excess returns. Simple returns in this case are reported returns net of all management fees. Second, the ranked portfolios are restructured every three, six and twelve months that serve as the three holding strategies. This will describe how ranked portfolio returns vary as we increase the post-formation periods. In the end, the portfolios are regressed against CAPM, the 4-factor model and the very recent 5-factor model by Fama and French (2015) to acquire risk-adjusted returns and alphas. If either top or bottom ranked portfolios show signs of generating abnormal returns, then its relative market efficiency may fail to hold as it introduces trading pattern that can be implemented and utilized in the financial world. Sharpe ratio is also computed in order to compare the reward to variability between the portfolios. In addition to describing risk-adjusted returns, we examine whether mutual fund managers possess any market timing abilities by applying a model of Henriksson and Merton (1981).

Next in line, contingency tables and post-formation on returns are constructed for each holding strategy. Similar to Carhart (1997), the purpose is to look at the historical probabilities of wind up in one ranking given an initial ranking and how returns behave throughout the sample period. Such approaches allow us to visualize patterns of persistent behavior and act as support to our main findings.

The key analysis discovers persistent underperformance in portfolio 6 and 7 given by their risk-adjusted returns and alphas, but the remaining portfolios show no significance. This states that the majority are not able to realize abnormal returns during the pre-defined time period, thus there is no real threat towards the market efficiency of the U.S. equity fund market. The results also suggest no market timing abilities that can be found. Furthermore, Carhart 4-factor model in general performs better in terms of explaining variation in risk-adjusted returns compared to CAPM and Fama and French 5-factor model in our sample size. As to rank dependency, the contingency tables illustrate persistent behavior in rankings in all holding strategies and strongest in three-months holding period. Finally, graphical representation of post-formation returns on ranked mutual fund portfolios demonstrates that the high returns in the top portfolios are short-lived.

Our thesis starts with important theories and research that relates to our research problem. This is followed by literature review in the same field of interest. An extensive data description will present all relevant parameters and descriptive statistics of importance. The ending covers final results and concluding remarks.

2 Theory

In the light of our thesis, persistence in mutual fund performance is the main subject of interest. In order to investigate this matter, it is necessary to understand a set of different performance measures and factor models that are currently available at our disposal. This section will present the development of some well-established theories in finance literature, discussing the underlying risk factors within a few of the most powerful models and provide a detailed walkthrough of the Efficient Market Hypothesis.

2.1 Modern Portfolio Theory & Capital Asset Pricing Model

Capital asset pricing model is essentially the building block for our topic, and can be treated as the mother of all models that is being used on this thesis. It is important to understand where CAPM originates from and why it is still widely used today for estimating cost of capital, asset pricing and evaluation of mutual fund performance in order to test for persistence within mutual funds.

CAPM was first introduced by financial economists; Jack Treynor (1961), William F. Sharpe (1964), John Lintner (1965) and Jan Mossin (1966). Each of them had built their work from the foundation of Modern Portfolio Management (MPT) by Harry Markowitz (1952). MPT assumes investors being risk averse with sole purpose of minimizing the variance of portfolio return, given expected return, and maximizing expected return, given variance.

As a result, Markowitz constructed the efficient frontier, which is a combination of individual assets that yield highest return given the level of risk. Thus, portfolios on the efficient frontier are considered as mean-variance efficient.

Figure 1: Efficient Frontier

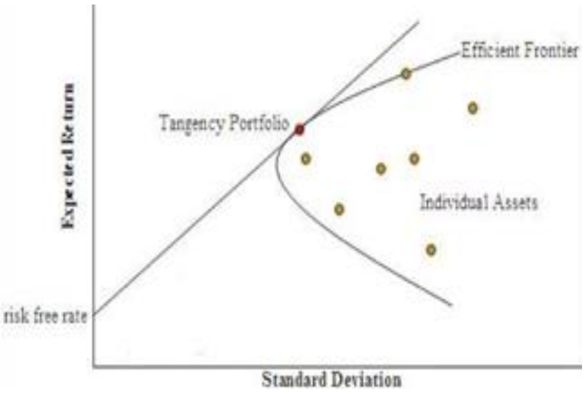


Figure 1 is an illustration of Markowitz model with the function of lending and borrowing at risk free rate. We have expected return on y-axis and standard deviation on x-axis. Assuming that we are able to borrow and lend at risk free rate, we obtain tangency point which is the market portfolio. Market portfolio is a portfolio that includes every type of assets in financial world where each asset is weighted in proportion to the entire value of the market. This is due to the fact that risk-free investments involve borrowing and lending among investors as both will cancel each other, respectively. Thus, we achieve market portfolio where all rational investors should hold their risky assets in the same proportion as their weights in the market portfolio.

The tangency line is known as capital asset line (assuming homogenous expectations), which is defined as:

$$R_p = R_f + \sigma_p \frac{(R_m - R_f)}{\sigma_m} \qquad (2.1.0)$$

This equation implies that the return of a portfolio is equal to the risk free rate plus a risk premium. Note that only efficient portfolios are on the CML (i.e. portfolios that do not possess any diversifiable risks).

CAPM is an extension of MPT. Since Markowitz model is only able to estimate the expected return or price on portfolios, CAPM is able to price absolutely any asset. Proving CAPM is outside the scope of this thesis, but CAPM exhibits the same assumption as MPT, including two additional key assumptions, that is the ability to borrow and lend at risk free rate and that all investors have homogenous expectations. In contrast to MPT, the CAPM equation is commonly defined as:

$$E(R_i) = R_f + \beta_{im}[E(R_m) - R_f] \qquad (2.1.1)$$

Where expected return on asset *i* is equal to risk free rate plus market premium times the sensitivity of expected return on asset to the expected return on market return, denoted as beta.

$$\beta_{im} = \frac{Cov(R_i, R_m)}{\sigma^2(R_m)} \qquad (2.1.2)$$

High value of beta indicates higher volatility, contrary to low value of beta implies low volatility, and beta of 1 gives a perfect linear relationship.

Figure 2: Security Market Line

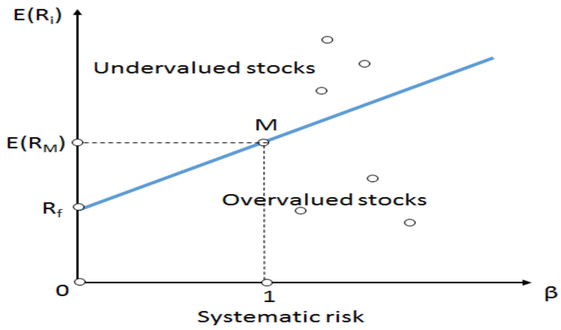


Figure 2 is a graphical representation of the notion embodied in CAPM. The difference between figure 1 and figure 2 is that CAPM provides different measurement. The line in figure 2 is known as security market line (SML), which graphs individual asset risk premiums as a function of beta. Contrary, CML graphs the risk premiums of efficient portfolios as a function of standard deviation. Note that SML is valid for both efficient portfolios and individual assets. CAPM states that investors should be only rewarded for systematic risk, and not unsystematic risk. In other words, an asset must increase its systematic risk in order to obtain higher expected returns. In addition, all securities that are fairly priced must lie on the SML in market equilibrium, implying stocks that deviates from SML are subject to mispricing.

2.2 Arbitrage Pricing Theory

Arbitrage opportunity occurs when an investor can make riskless profit without making a net investment. It is an exploitation of price differences of identical or similar financial instruments on different markets or in different forms. Mispriced securities are a result of market inefficiencies where arbitrage is considered as a mechanism that restores prices to be in equilibrium on the long run. Arbitrage pricing theory (APT) was first proposed by the economist Stephen Ross (1976). APT is somewhat very similar to CAPM, but differs from the CAPM by being less restrictive on its assumptions. Arguably, CAPM may be regarded as a special case of APT, in the sense that security market line obtained by CAPM represents a single-factor model of the asset price. In contrast, arbitrage pricing theory is commonly associated with multifactor model, defined as:

$$r_i = E(r_i) + \beta_{i1}F_1 + \beta_{i2}F_2 + \beta_{i3}F_3 + \beta_{ik}F_k + e_i \qquad (2.2.0)$$

Where return on security i is equal to previously expected value, $E(r_i)$, plus macro factors (surprises), F, times the sensitivity of security relatively to the systematic factors, β_i, and firm-specific events e_i. Note that the arbitrage-pricing model does not contain any form of specific "theory" in the equation. Intuitively, it only relies on the principle of law of one price where it states as: "If two assets are equivalent in all economically relevant respects, then they should have the same market price" (Bodie, Marcus and Kane 2014). However, we need to define the origination of $E(r_i)$, which requires a theoretical model of equilibrium of security returns. $E(r_i)$ is essential the variable from our previous discussion, namely SML from CAPM.

$$E(r_i) = r_f + \beta_{im}[E(r_m) - r_f] \qquad (2.2.1)$$

By substituting the risk premium of the market portfolio, we can rewrite it as:

$$E(r_i) = r_f + \beta_i RP_m \qquad (2.2.2)$$

As stated earlier, we can now see that CAPM is just a single-factor model. Furthermore, APT assumes that the unsystematic risk, e_i (2.2.0), is uncorrelated with assets and any systematic risk factors. Next part follows a set of rules and proofs, which are beyond our thesis objective, but we would like to summarize the main important features; adding concept of well-diversified portfolio and tracking portfolio into equation, it transforms into our desired APT model:

$$E(r_i) = r_f + \beta_{i1}\lambda_1 + \beta_{i2}\lambda_2 + \beta_{i3}\lambda_3 + \beta_{ik}\lambda_k \qquad (2.2.3)$$

Where λ_k is the risk premium of pure factor portfolio i (pure factor = a portfolio with beta of 1 to the factor and beta of 0 to all other factors). Arbitrage occurs when the expected return of a tracking portfolio differentiates from the expected return on the tracked investment, i.e. equation (2.2.0) yields different results than equation (2.2.3).

Why APT matters? First of all, it may be considered as a revolutionary model in the sense that it allows user to customize the model to the security being analyzed. The model does not require the benchmark portfolio in CAPM to be the true market portfolio, but can be any well-diversified portfolio, which leads to higher flexibility. APT allows multiple sources of risk to explain the variation of an asset's return and mainly uses arbitrage arguments as key driver.

The market portfolio is well defined conceptually by CAPM. In APT, the factors are not well specified; hence it may be complicated to determine explanatory risk factors that create equilibrium relationship with an asset's return. Arguably, it may be close to impossible to detect absolutely every influential factor, and the more betas we estimate, the more statistical noise we include. APT is important to our thesis, as the models we are testing are in fact multifactor models, with different systematic risk factors. As stated earlier, multifactor models expect that there should be no presence of arbitrage opportunity, even with a violation; it will create strong market forces to pressure it back to equilibrium.

2.3 Jensen's Alpha

Security market line provides a benchmark for the evaluation of investment performance. Succession of superior management is dependent on finding and picking stocks that are undervalued. A common method is to use Jensen's Alpha

(1968) as a tool of performance measurement, which is the difference between the actual and predicted returns.

$$r_p = \alpha_p - [r_f + \beta_{im}(r_m - r_f)] \qquad (2.3.0)$$

Jensen applied CAPM into a performance framework for different equities like stocks, portfolios and mutual funds. The only way mutual fund can possess superior performance, it needs to realize a higher return relatively to the model's prediction. The intercept of the model serve as the measure of performance reflected by equation (2.3.0). Positive alpha implies superior performance and negative indicates underperformance. CAPM states that if the stock assets are priced rationally, the expected value of alpha is zero for all securities, as the expected return of manager's portfolio should not plot above the security market line (Figure 2) in an efficient market. Thus, returns that deviate from SML may indicate superior performance/underperformance, or simply due to luck if not consistent. Burton Malkiel (1995) found evidence of slightly negative but not significantly different from zero. On average, active mutual funds does not outperform the market index on a risk-adjusted basis.

2.4 The Sharpe Ratio

William Sharpe (1966) proposed a measure of reward to variability named Sharpe ratio, built on the Markowitz mean variance paradigm and is a direct extension of Treynor's work (1965). The difference between Treynor and Sharpe ratio is the risk denominator, as Treynor is based on beta while Sharpe is based on the average standard deviation of the portfolios being measured. Essentially, the Sharpe ratio measures excess return of the portfolio against the total risk assumed by the portfolio.

$$S_p = \frac{E_{r_p} - R_f}{\sigma_p} \qquad (2.4.0)$$

The Sharpe ratio is famous for its simplicity that can be applied to compare the risk and return of single stocks, mutual funds, portfolios and vast amount of other investment strategies. As to the total risk assumed by the portfolio, the Sharpe ratio considers both systematic risk and unsystematic risk, although the unsystematic risk is often eliminated through diversification.

However, the Sharpe ratio has some limitations. First, as it uses standard deviation of a portfolio to determine its risk, it automatically assumes normal distribution. Skewed distributions with rare occurrences could therefore result in inflated Sharpe ratios that do not address the whole story about the volatility of the investment. Second, it fails to differentiate between upside deviation and downside deviation. In other words, the Sharpe ratio treats all volatility the same as it penalizes strategies that have upside volatility (positive returns) in its formula when in fact it should not. Lastly, standard deviation does not take into account the timing of returns.

2.5 Fama and French 3-Factor Model

Although CAPM upheld its popularity for decades, anomalies continued to challenge the fundamentals of the model. Several researchers such as Keim (1983), Banz (1981), Friend and Blume (1973) and Fama and French (1992) found evidence of funds concentrating on low-betas, small-firms and value stocks frequently generate positive abnormal returns comparative to the CAPM expectations, even when fund managers did not possess superior stock picking skills. CAPM estimates for high-beta stocks are too high, and estimates for low-beta stocks turn out to be too low. Firms with small market capitalization produced higher returns than predictions of CAPM. Fama and French (1993) designed a factor based on this anomaly named SMB (small minus big). Another pattern that deviated from the laws of CAPM was the book-to-market effect. It was found that stocks with high book-to-market ratio tend to outperform and stocks with low book-to-market ratio underperformed, thus HML (high minus low) was introduced. The underlying reason of implementing the new factors is similar to the market factor of CAPM. Higher returns are compensation for higher volatility. Thus, these two new factors are supposed explain these anomalies that have significant explanatory power in the variations of cross-sectional returns that deviate from CAPM equilibrium. The 3-factor model is described as:

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + e_{it} \qquad (2.5.0)$$

The underlying risks of SMB and HML are not completely explained by Fama and French. However, they do come with some reasonable ideas. As HML focuses on firms with high book-to-market ratios, by its nature, this may imply that the market value of a firm has been decreasing below its respectively book value prompted by unfavorable news and resulting into financial distress. Hence, it is plausible to demand higher risk premium. As for SMB, the underlying risks of small firms are known to be more volatile than large firms due to cash-flow uncertainties or other type of strategic risks that exhibits within small firms. Thus, by concentrating small firms require higher risk premium. These are only some possible explanations out of many, as there is still no general consensus on the risk interpretation of the factors.

Furthermore, Eugene F. Fama and Kenneth R. French (2004) argued that due to the strictness of CAPM; it fails to capture entire risk-return relationship. For instance, the market portfolio cannot be observed, which CAPM revolves around, thus at best we need to use proxies such as S&P 500 and hope that it is sufficiently close enough to the true unobservable market. The empirical failings are serious enough to invalidate most applications of the CAPM. Nonetheless, CAPM is a fundamental concept of portfolio theory and asset pricing, in which more complicated models originate from. If the coefficients to the three factors capture all variation in expected returns, the estimated intercept is then zero for all securities and portfolios that are being measured.

2.6 Carhart 4-Factor Model

The momentum anomaly was first widely recognized in the finance literature through Hendricks, Zeckhauser and Patel (1993) and Jegadeesh and Titman (1993). In the latter paper, they find a pattern where winner stocks remain as winners and loser stocks remain as losers in short consecutive of time. By utilizing such anomaly, riding the momentum investing wave by buying last period winners and selling last period losers tend to yield significantly higher returns. They argued that the effect of deferred responses on new information contributes to the anomaly, but emphasize that further research on behavioral finance is required before providing any absolute conclusions. Daniel, Hirshleifer and Subrahmanyam (1998) propose that investors may suffer from overconfidence and lead them to overweight private information signals and underweight public information signals that result in trends. Hong and Stein (1999) suggest that short-term price momentum is a result of under-reaction to information as information diffuses slowly across news watchers. Barberis, Shleifer and Vishny (1998) model is also based on a short-run under-reaction. They conclude that price momentum is analogical to positive autocorrelation in stock returns, which could arise because of investors' under-reaction or continuing overreaction to news. In summary, the theories suggest that investors do not fully or correctly incorporate stock news immediately and subsequently cause inertia in the market reactions.

The underlying risk of momentum is somewhat harder to interpret than the 3-factor model. There are no general recognitions on this matter and the proposed explanations are at its very best questionable. One of the suggested explanations is that momentum exposes investors to extreme losses in certain situations, known as "tail risk". Daniel, Jagannathan and Kim (2012) argued that even though momentum strategies, on average, offer high gross returns with little systematic risk, they are exposed to infrequent but rather huge losses. In his sample of 978 months, there were 13 months (all of them occur during turbulent months) with losses exceeding 20%/month. By comparing cumulative return of momentum factor and market risk factor as shown in figure 6 (Section: Data – Regression Factors), we can observe some striking implications. During one of the biggest financial crisis in 2008, the market experienced economic pitfall, while momentum strategies somehow still generated positive returns. However, in the recovery state of the global economy, momentum strategies plummeted significantly more than the rest of the fundamental factors. This unique observation can also be seen during The Great Depression, Dot-com bubble/crash and other economic turbulent years. This is consistent with the previous suggestions and findings of behavioral models as momentum is relied on riding trends.

Carhart (1997) constructed a momentum factor that captures this anomaly, and incorporated into the Fama and French 3-factor model. He argues that the inclusion of the momentum factor, PR1YR (prior one year), significantly improves the explanatory power of the model relative to the CAPM and the 3-factor model. Essentially, this reduced the error term in risk-adjusted returns obtained by the model. The estimated intercept (alpha) is the measure of performance.

$$r_{it} = \alpha_{iT} + b_{iT}RMRF_t + s_{iT}SMB_t + h_{iT}HML_t + p_{iT}PR1YR_t + e_{it} \quad (2.6.0)$$

2.7 Fama and French 5-Factor Model

Despite the well-established and acknowledged 3-factor model within academia, Fama and French (2015) added two additional factors, namely profitability and investment. The reasoning for the inclusion of the two quality factors is partially due to the empirical evidence presented by Novy-Marx (2012), Titman and Wei and Xie (2004) who showed that the three-factor model failed to capture much of the variation in average returns related to investment and profitability. The former factor (profitability) is the return spread of the most profitable firms minus the least profitable. The latter factor (investment) is the return spread of firms that invest conservatively minus aggressively. The model is presented as:

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_iSMB_t + h_iHML_t + r_iRMW_t + c_iCMA_t + e_{it} \quad (2.7.0)$$

There is some criticism concerning the new model ignoring momentum factor as it is widely accepted and been around for 20 years. Furthermore, it is also shown that the value factor HML becomes redundant for describing average returns when profitability and investment factors have been added into the equation were sole interest is abnormal returns. However, the results of this new model with or without HML shows that it manages to explain between 69% and 93% of the cross-section variation in expected returns for the size, book-to-market, profitability, and investments portfolios being examined.

Fama and French (2015) argued that the main drawback of this model lies within its failure to capture the low average returns on small stocks whose returns perform like those of firms that invest a lot despite of low profitability, as well as the model's performance being indifferent to the way its factors are defined.

The 5-factor model is regarded as relatively new and is still being tested in the field of finance. Arguably, it has more or less proved to be a slight improvement compared to the previous models, but has also left room for better models to be further developed from it. In the light of our thesis, the intercept of the regression serves as the measure of performance. We will conduct a comparable analysis between all the models presented (CAPM, Carhart 4-factor and Fama-French 5-factor) in order to find the best fit model that investigates persistence in mutual fund performance.

2.8 Market Timing Model

As mentioned earlier, one of the most common methods to evaluate fund performance is through the intercept of a regression analysis, namely alpha. However, alpha only captures the level of stock picking skills, and not any other potential abilities/skills that can empower mutual fund performance, such as market timing ability. Hence, it is our interest to examine persistence in the market timing ability of mutual fund managers. Henriksson and Merton (1981) constructed following regression model to detect market timing:

$$R_{it} - R_{Ft} = a_i + \beta_i(R_{Mt} - R_{Ft}) + \gamma_i(R_{Mt} - R_{Ft})D + e_{it} \qquad (2.9.0)$$

The idea is to know when to employ a high market beta or predict the future market price movements. One should take risk (high beta, and possible systematic risk) when stocks are cheap, and reduce risk (low beta, low systematic risk) when stocks are expensive. Naturally, these characteristics are reflected on the market risk premium; we test whether mutual fund managers invest in the market portfolio when its risk premium is high and exit the market when its risk premium is low or negative (zero), measured by γ_i. D is the dummy variable that equals to 1 when $R_M > R_f$ and equals to 0 when $R_M < R_f$.

According to the Efficient Market Hypothesis, asset prices cannot be predicted with consistency as random walks always persist in financial markets. It has also been sensible to conduct a market timing strategy in certain circumstances, like an apparent bubble. The underlying risk of such strategy is that the uncertainty of correction of market prices is high; it can be costly to bet against the market if the equilibrium forces do not act in the near future.

Most studies on market timing in mutual funds discover significant ability in only a handful of funds. The amount of successful market timers found by these studies

(Treynor and Mazuy (1966), Henriksson (1984)) is more or less consistent with the number expected under the null hypothesis. Bollen and Busse (2005) study the short term persistence by using daily data and finds that only top decile (ranked by past simple returns) exhibit significant persistence within market timing, as all negative significant coefficients are equivalent to no market timing ability.

2.9 The Efficient Market Hypothesis

A market is said to be efficient when asset prices reflect all available information. According to this hypothesis, when new information about an asset becomes available, its price should quickly adjust to the market's consensus estimate of its value (Bodie, Marcus and Kane 2014).

This theory still plays a central role in modern finance. The early stages of the theory originate from Fama's thesis "Random Walks in Stock Market Prices" (1965). In this article, he challenged the procedures for predicting stock prices by "technical" or "chartist". Naturally, if the random walk theory is an accurate description of reality, then chartists who actively use previous returns as their core trading scheme (technical analysis), adds absolutely no actual value to investors. This also applies for fundamental analysis, as it only adds value when the analyst has new information or insight which was not fully incorporated in current market prices.

Fama (1969) established his reputation through his paper on market efficiency. Essentially, he introduces three stages of market efficiency, in which each one is well-defined and distinguished based on the information form that is obtainable; weak, semi-strong and strong form.

Weak form asserts that prices already reflect all information regarding market trading data such as historical prices and trading volume. This implies that it is practical impossible to add more value by using past returns, since the data available is considered as common insight. Next, the semi-strong hypothesis states that all publicly available information regarding the prospects of a firm must be reflected in the stock price. In addition to historical prices and trading volume, this includes balance sheet composition, quality of management and earnings forecasts. If investors have information regarding this, it is assumed to be already incorporated in the stock price. Testing is therefore based on the efficiency of price adjustments towards new published information. The strong form is the most extreme hypothesis, stating that stock prices reflect all information relevant to the firm, including information that only company insiders have knowledge of (private information). In other words, trading on private information gives no advantages or benefits to investors.

Fama (1969) concluded that the market is efficient on average. Several methods were applied to test the efficiency of the weak and semi-strong-form and both remained intact. Back testing was implemented for the weak form based on trading algorithms of past returns, but no significant profits were found. Hence, the weak form could not be rejected. Event studies were applied to examine the semi-strong efficiency, and it was found that nearly all significant information was embodied in the price within the defined timeframe. As to the strong-form efficiency, it did not satisfy the assumptions and performed relatively worse. In fact, this is expected, since this hypothesis is the most extreme case. It was rather two important issues that rejected the strong form hypothesis, namely corporate insiders and specialists/market makers. The former is self-explanatory, while the specialists manage limit orders and execute major exchanges that can influence the market prices significantly. It is noteworthy to mention that the Efficient Market Hypothesis is still being investigated aggressively by academics with an attempt to invalidate the theory. Nevertheless, the theory manages to uphold its ground and was considered to be quite accurate in a well-functioning market.

This particularly theory is important to persistence in mutual fund performance. If patterns or trends are observed to be persistent over time, then it is possible to utilize this to predict future price movements and earn abnormal returns. This is a direct test on the weak form of market efficiency, i.e. if we find significant persistence, we reject the weak form. Thus, our forthcoming analysis will primarily focus on how past performance of mutual funds will affect the future performance. In practice, the findings may allow professional and non–professional investors to become more competent on their investment decisions when encountering mutual funds that aggressively use their track record as recommendation.

3 Literature Review

The previous studies that we found of most importance related to our research topic are briefly summarized in the next paragraphs, where we include studies both for and against active management and most recent studies on new multifactor models.

As implied by the Efficient Market Hypothesis (Fama 1970), mutual funds should not be able to outperform the market and yield abnormal returns. It has been shown that the EMH held up well with very few exceptions; if the managers possess superior information, they might get competitive advantages and perform better than the selected benchmark.

3.1 Research in Favor of Passive Management

In 1984, Roy Henriksson (1984) applied the basic model of market timing developed by Merton (1981) to 116 open-end mutual funds for the period 1968-80. The empirical results do not support the hypothesis that fund managers are able to follow a strategy that successfully times the return on the market portfolio. Only three funds of the 116 had significantly positive estimates of market timing and only one fund were significant in both sub periods when the sample was split in half.

According to Malkiel (1995) who studied mutual fund performance from 1971 to 1991, concluded that most investors would be better off by purchasing a low expense index fund than buying an active mutual fund. Active management generally fails to provide any abnormal returns and investing in an active fund has a higher tax burden for the investor. Malkiel also found that mutual funds tend to underperform the market, even before the management expenses have been accounted for.

In their paper "*Luck versus Skill in the Cross Section of Mutual Fund Returns*", Fama and French (2010) concluded that mutual fund investors in aggregate, yield net returns that underperform their benchmarks by about the same as the costs in expense ratio. This implies that if there is in fact existence of managers with superior stock picking skills, it is hidden in the aggregate results by the performance of managers with insufficient skills. They also tested 3156 individual funds, and found that only a few funds have enough skill to cover costs when corrected for luck.

Barras and Scaillet (2010) applied a new method to distinguish between skilled and unskilled fund. They found that the amount of skilled managers has diminished rapidly over the past 20 years, while the amount of unskilled managers has substantially increased. Most actively managed funds provide either positive or zero net-of-expense alphas, which make them at least equal to passive funds. The main reason for actively managed fund's underperformance is due to the long-term survival of a minority of truly underperforming funds.

Carhart (1997) constructed a 4-factor model that incorporated Jegadeesh and Titmans momentum factor (1993) into the Fama-French 3-factor model (1993). He measured mutual fund performance and found that funds with high past alphas generate relatively higher alphas and expected returns in the subsequent period. However, these results are exposed to model misspecification, since the same model is applied to rank funds in both periods. Furthermore, the higher expected alphas are not significant different from zero. In other words, the top mutual funds are at best able to earn back their investment expenses with higher gross returns. Overall, Carhart's study is consistent with market efficiency, and most funds underperform by approximately the same as their investment expenses with the bottom-decile underperforming twice of their reported investment costs. Hence, the costs consume all superior gains and the results do not support the existence of skilled or informed mutual fund portfolio managers.

3.2 Research in Favor of Active Management

Article by Gruber (1996) explains why investors buy actively managed open end mutual funds, when in fact mutual funds, on average, offer a negative abnormal return and that investor usual gets better outcome by investing in index funds. Gruber argued that future performance is in part predictable from past performance, because the price of a fund does not reflect whether or not it has superior management. A group of well-informed investors seems to recognize this and benefit from it, since those funds outperform the average active and passive funds.

Grossman and Stiglitz (1980) argued that a state where all information is available with no presence of arbitrage opportunities is not obtainable, thus one should not expect that security prices fully incorporates information possessed by informed individuals. They believed there are arbitrage opportunities for those who were able to acquire superior information, given that the return of the arbitrage opportunity is higher than the cost of acquiring the information. Hence, we should expect some mutual fund managers to possess informational advantages, at least for some time period.

In an article by Wermers (2000), he used data from 1975 to 1994 and measured the performance of the mutual fund industry. He found that the mutual funds held stock portfolios that outperformed a broad market index by 1.3% per year, whereas 70bp is due to superior stock picking skills. However, on a net-return level, the funds underperform by 1% per year. The main reason for this is the transaction costs and expenses. Their studies also exclude the tax benefits you would get from passive index funds.

Bollen and Busse (2005) studied persistence in mutual fund performance emphasizing short measurement periods. They ranked funds every quarter by their risk-adjusted return measured over a three-month period. Over this short horizon they found evidence of persistence using the 4-factor model for the top decile funds. The results are robust across the momentum factors, which contradicts Carhart's result, who found no evidence of superior ability after controlling for the momentum anomaly in his paper from 1997.

3.3 New Multifactor Models

More recent studies have tried to improve on the existing factor models created by Carhart and Fama and French. Hou, Xue and Zhang (2015) examined close to 80 anomalies and found two major implications. First, one-half of the anomalies earn insignificant average returns, which indicate that many claims in the anomalies literature seem exaggerated. Second, they created an empirical model consisting of the market factor, a size factor, an investment factor, and a profitability factor. They called it the q-factor model, and it arguably outperformed the original Fama-French 3-factor model and Carhart's 4-factor model in capturing significant anomalies that summarize cross section of average returns.

Since the creation of the well-known 3-factor model by Fama and French back in 1993, it has received significant amount of criticism by numerous researchers, such as Novy-Marx (2012) and Titman, Wei and Xie (2004). They criticized that the model were unable to capture much of the variation in average returns related to significant risk factors, namely investment and profitability. Thus, Fama and French responded by introducing a 5-factor model (2015) with the inclusion of these two independent variables. They argued that this model performed better than the 3-factor model, as they found significant patterns in average returns related to size, book-to-market, profitability, and investment. However, with the addition of profitability and investment factors, the value factor (HML) of the original Fama and French 3-factor became redundant for describing average returns in the sample they examined.

4 Methodology

A framework that combines Carhart (1997) and Bollen and Busse (2005) are applied to study persistence. The funds are sorted and ranked into ten equally weighted portfolios built from the mutual funds lagged one-year simple returns. Simple returns are reported returns net of all management fees. The ranked portfolios are further reconstructed every quarter, semi-annual and annual. The returns are risk-adjusted by using CAPM, Carhart 4-factor model and Fama and French 5-factor model. In addition, the market timing model of Henriksson and Merton (1981) is applied to see whether the fund managers possess market timing abilities. Contingency tables are based on the sorting procedure and are composed to uncover any potential trends in rank dependency.

4.1 Capital Asset Pricing Model

The Capital Asset Pricing Model developed by Sharpe (1964), estimates the risk-adjusted return of an asset. The CAPM is commonly presented as:

$$E(R_i) = R_f + \beta_{im}[E(R_m) - R_f] \tag{4.1.0}$$

$E(R_i)$ is the expected return of asset i.

R_f is the risk-free rate of return.

$E(R_m) - R_f$ is the market's risk premium.

4.2 Carhart 4-Factor Model

$$r_{it} = \alpha_{iT} + b_{iT}RMRF_t + s_{iT}SMB_t + h_{iT}HML_t + p_{iT}PR1YR_t + e_{it} \quad (4.2.0)$$

r_{it} is the return on a portfolio in excess of the risk-free rate.
RMRF is the excess return on a value-weighted aggregate market proxy.
SMB, HML and PR1YR are returns on value-weighted, zero-investment, factor-mimicking portfolios for size (small minus big), book-to-market, and one-year momentum in stock returns.

This model is constructed by using Fama and French 3-factor model including an additional factor from Jegadeesh and Titman's (1993) one-year momentum anomaly.

4.3 Fama and French 5-Factor Model

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_iSMB_t + h_iHML_t + r_iRMW_t + c_iCMA_t + e_{it} \quad (4.3.0)$$

RMW_t is the difference between the returns on diversified portfolios of stocks with robust and weak profitability.
CMA_t is the difference between the returns on diversified portfolios of stocks of low and high investment firms.

The 5-factor model was created as a result of empirical evidence presented by Novy-Marx (2012), Titman, Wei and Xie (2004) who showed that the 3-factor model failed to capture much of the variation in average returns related to investment and profitability.

4.4 Henriksson and Merton Market Timing Model

$$r_{it} = \alpha_{iT} + b_{iT}RMRF_t + c_{iT}RMRF_t * D + e_{it} \quad (4.4.0)$$

r_{it} is the return on a portfolio in excess of the risk-free rate.
RMRF is the excess return on a value-weighted aggregate market proxy.
D is a dummy variable that equals 1 when $r_m > r_f$ and zero otherwise.

This model was created by Henriksson and Merton (1981) with the purpose of detecting market timing ability. The model is then modified to incorporate the explanatory variables in Carhart 4-factor and the Fama and French 5-factor to find the best fit model to capture market timing ability.

4.5 Persistence

In the essence of our thesis, the main approach used to study persistence in performance is a combination of the methods used by Carhart (1997) and Bollen and Busse (2005). That is to create ten synthetic portfolios and rank them from best to worst based on the one-year moving average. If top or bottom ranked portfolios exhibit significant abnormal returns, then persistence in performance is confirmed.

The evaluation period is essential in the case of mutual fund performance. Hendricks et al. (1993) included several different evaluation periods and concluded that one year period produced the strongest empirical results. Carhart (1997) also used one year interval, as a shorter time period may experience autocorrelation when using monthly data. Since our dataset is based on monthly data, time-length of one year is therefore preferred.

The next step regards the sorting framework. Mutual funds will be placed into ten different portfolios in which each represent a decile; the ranking is based on lagged one-year simple returns. In the setting of performance analyses, using equally weighted portfolios is considered as the most common procedure. Pension funds and corporate funds would dominate the portfolios if a value weighted approach were applied. Since this analysis is designed to measure mutual fund performance in general, using equally weighted portfolios is the optimal choice.

As mentioned, Carhart (1997) arranges the portfolios based on lagged one-year reported returns of the mutual funds and reform them every year. In our forthcoming analysis, the one year holding period will be replicated, but three and six months holding periods are also examined in order to test for short-term persistence. Studies have shown that mutual fund performance could be short-lived due to the competitiveness of the mutual fund market (Bodie, Marcus and Kane (2014)).

Consistency in ranking is a visual sign of persistent behavior in returns. If the funds in portfolio 1 (top decile) in one period maintain its ranking in the following period(s), then it is said to be a sign of consistent ranking. Carhart (1997) constructed contingency tables to illustrate this. The table shows the probability of ending in portfolio *j* given initial portfolio *i*.

4.6 Performance Measure - Jensen's Alpha

Jensen (1968) proposed a measure for the performance of a portfolio based on the Capital Asset Pricing Model (CAPM) that aims to determine abnormal returns.

$$\alpha_p = \left(R_p - R_f\right) - \beta_{im}\left(R_m - R_f\right) \qquad (4.5.0)$$

If the alpha of a portfolio is statistically significant, it would imply that the fund is able to earn abnormal returns. CAPM, Fama and French 3-factor and Carhart 4-factor model has been heavily used to measure Jensen's alpha, we will in addition to these models use a new model, Fama and French 5-factor model.

4.7 Performance Measure – Sharpe Ratio

Sharpe (1966) introduced the risk-adjusted performance measure known as the Sharpe ratio. It shows the reward to an investor is compensated with relative to the total risk in his portfolio.

$$S_p = \frac{E_{r_p} - R_f}{\sigma_p} \qquad (4.6.0)$$

S_p is the Sharpe ratio of portfolio *p*.

E_{r_p} is the expected return of portfolio *p*.

r_f is the risk-free rate.

σ_p is the standard deviation of portfolio *p*.

Essentially, an investor would like to achieve the highest possible Sharpe ratio by maximizing his excess return given the volatility or minimizing his volatility given the excess return. This type of measure entails some weaknesses that have been discussed in section 2.4 (Theory – The Sharpe Ratio). Sharpe ratio is solely used to compare the risk-adjusted return given by our sorted portfolios.

5 Data

In this section, we will emphasize the data applied in our performance analysis. The historical mutual funds returns and fees are gathered from Bloomberg and the risk-factors from publically accessible sources (Kenneth R. French Data Library).

5.1 Fund Selection

The dataset contains monthly return for 1376 open-ended US mutual funds. The funds are all registered in US and invest primarily in US equity. The dataset consists of actively managed funds that aim to realize positive abnormal returns and exclude funds that are tracking specific indices. In addition, the sample comprises solely on funds that are still alive today, and thus it faces the issue of survivorship bias. It is reasonable to believe that this will have an upward bias on the regressions results presented. This issue will be discussed more thorough later.

5.2 Time Period

The time period is from January 2000 to December 2015. We chose this specific window in order to test for persistence up to the most recent period where data is available. In addition, we want to compare our results with previous findings at earlier stages of the financial market regarding mutual fund performance. Fifteen years of monthly data on each fund should satisfy more than the minimum statistical requirements. However, our sample size consists of two rather apparent crashes, namely the Dotcom and the Subprime Mortgage in 2000-01 and 2008. This particular phenomenon could results to extreme observations and creates wrong impressions of the mutual fund market. Simply removing the outliers may also affect the likelihood of conducting type I and type II errors. There is to our knowledge no clear remedy on this problem and decided to keep all observations as it is. In total, we have a time series of 180 months with 1376 funds.

5.3 Benchmark

Finding an appropriate benchmark is vital in the models presented in later sections. It should reflect as much as possible of the fund’s variation in returns, given that the true market portfolio is unobservable, the best fit benchmark index will serve as the market proxy.

This dataset contains 1376 mutual funds and they all have the freedom to choose their own benchmark, meaning that we have a wide variety of benchmark indices which in return can be problematic and time-consuming when applying each single of them to three different models. Fortunately, this thesis focuses on persistence and performance on aggregate level and not the performance of individual funds. Thus, a common market proxy is more applicable. The market factor constructed by Fama and French will be chosen for this purpose as it best reflects the investment universe of the sample funds. It includes firms incorporated in the US that is listed on NYSE, AMEX and NASDAQ.

5.4 Risk-Free Rate

The models presented in later sections applies the portfolios excess return as the responding variable and the market excess return as one of the independent variables. In other words, portfolios return and market proxy less the risk-free rate. In real world, there are no assets that can realize returns absolutely riskless. Therefore, a proxy is needed and the most frequently used for this objective is Treasury bills (Bodie, Kane, & Marcus 2014). Researchers such as Fama and French (1993) and Carhart (1997) used one-month Treasury bill as the proxy for the risk-free rate. As our dataset are based on monthly returns, one-month T-bill has also been chosen as the most appropriate proxy, which is obtained from Kenneth R. French Data Library.

5.5 Regression Factors

The market factor is the market's risk premium (benchmark net of risk-free rate). The remaining factors used in this thesis, small minus big, high minus low, momentum, investment and profitability are described in more depth in section *4. Methodology*. Once again, these factors are collected from Kenneth R. French Data Library.

5.6 Survivorship and Incubation Bias

As mentioned, our sample size is limited to mutual funds that are operative today. Mutual funds that perform poorly entail higher probability of being terminated (Carhart (1997)). This fact might give our dataset a slight upward bias as it does not contain the funds that has been dismissed.

Wermers (1997) states that survivorship bias is considered to be a relative small problem, as he did not find significant differences in returns between the surviving funds and the entire fund market. Malkiel (1995) finds that excluding non-surviving significantly biases the empirical results. Unfortunately, our dataset will contain some traces of survivorship bias.

Incubation is a trial process in which a fund company uses its own capital or employee capital to operate several funds privately, and only opens the top performing fund to the public. This pre-release return is included in mutual fund databases. Evans (2010) found that funds in incubation generated higher risk-adjusted returns than non-incubated funds, which may also lead to a bias in the sample. Although considering the amount of funds we have in our sample, the potential effect is assumed negligible.

5.7 Descriptive Statistics

The following part will present statistical analysis on the key variables based on historical features and study the descriptive of the ranked portfolios.

5.7.1 Overall Returns

The equally weighted portfolio in this part consists of all the funds in the sample net of management fees. The monthly excess returns are then computed as an arithmetic average. It is ranging from January 2001 to December 2015, where first month of the portfolio's construction marks the starting date. The portfolio is based on the one-year moving average described earlier.

Table 1: Equally weighted portfolio of all funds & benchmark descriptive statistics

Portfolio	Monthly excess return	Std.Dev.	SR	Max	Min	Kurtosis	Skewness
All funds (EW)	0,44 %	4,64 %	9,40 %	12,27 %	-20,19 %	1,8232	-0,7006
MKT-RF	0,43 %	4,45 %	9,66 %	11,35 %	-17,23 %	1,0746	-0,5954

All numbers are based on monthly returns in the time period 2001:01 - 2015:12

The equally weighted (EW) portfolio has slightly higher excess return and standard deviation, but offers lower Sharpe ratio (SR) compared to MKT-RF. The max and min adds some detail to this, showing that the EW portfolio has a higher max but also a lower minimum compared to the MKT-RF. But in terms of performance, the EW portfolio performs pretty much the same as the benchmark index. This confirms that a well-diversified portfolio (zero unsystematic risk) can serve as the market portfolio.

5.7.2 Ranked Portfolios

There are a few interesting observations on the ranked portfolios in twelve-month holding strategy. The monthly excess return is descending accordingly from the top to bottom portfolios and range from 0,71% to 0,07%. The Sharpe ratio (SR) roughly exhibit similar pattern as the monthly excess return. The top portfolios yield highest SR of 13,50% and the bottom ones yield lowest SR of 1,18%. Furthermore, the skewness of all portfolios is slightly skewed to the left, which means that the long tail is on the left hand side. This could be due to the fact that the absolute values are much larger in minimum values compared to maximum values.

Table 2: Descriptive statistics on ranked portfolios

				Twelve-month			
Portfolio	Monthly Excess Return	St.Dev.	SR	Max	Min	Kurtosis	Skewness
1A	0,71 %	5,48 %	13,03 %	13,22 %	-27,61 %	3,9392	-1,1629
1	0,69 %	5,12 %	13,43 %	13,83 %	-25,44 %	3,8029	-1,1351
2	0,63 %	4,68 %	13,50 %	14,14 %	-20,78 %	2,3293	-0,8024
3	0,53 %	4,66 %	11,47 %	13,91 %	-19,61 %	1,9146	-0,6827
4	0,46 %	4,59 %	9,97 %	12,17 %	-19,12 %	1,6375	-0,7196
5	0,44 %	4,61 %	9,59 %	12,69 %	-19,49 %	1,7055	-0,6749
6	0,39 %	4,54 %	8,59 %	12,46 %	-18,65 %	1,3684	-0,6052
7	0,33 %	4,58 %	7,19 %	12,40 %	-18,40 %	1,1716	-0,5605
8	0,28 %	4,57 %	6,15 %	12,65 %	-18,88 %	1,4617	-0,5973
9	0,33 %	4,79 %	6,93 %	14,59 %	-19,64 %	1,5440	-0,5781
10	0,28 %	5,39 %	5,13 %	15,66 %	-21,87 %	1,5853	-0,4657
10C	0,07 %	6,31 %	1,18 %	17,52 %	-26,39 %	1,5999	-0,4644
1 - 10	0,41 %	3,45 %	11,91 %	11,56 %	-10,54 %	0,8919	-0,3041
All funds (EW)	0,44 %	4,64 %	9,40 %	12,27 %	-20,19 %	1,8232	-0,7006

All numbers are based on monthly returns in the time period 2001:01 - 2015:12

The three holding strategies are very similar with the only differences of higher monthly excess returns and more frequent rebalancing, but they tell the same story. Thus, the remaining holding strategies are presented in the appendix (table 11 & 12) for further details.

A graphical representation describes the findings easier in the figures below, whereas cumulative returns on all portfolios are plotted against the sample time series. As one can observe, the cumulative returns are ascending quite significantly from the twelve-month to six-month and six-month to three-month holding periods.

Figure 3: Cumulative returns on ranked portfolios with twelve-month holding period

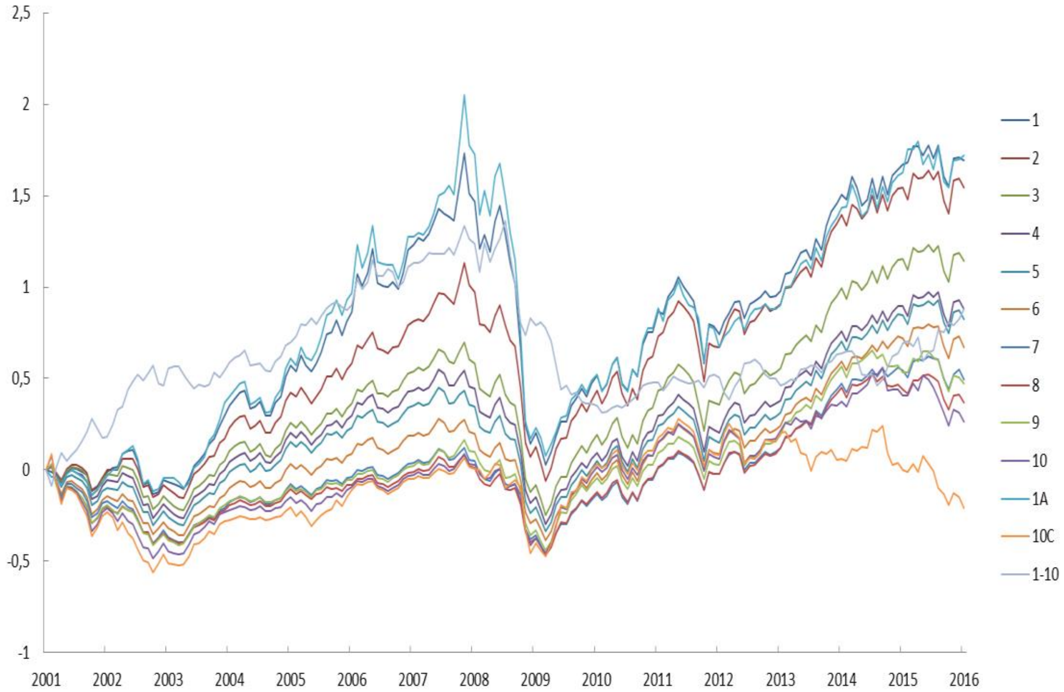


Figure 4: Cumulative returns on ranked portfolios with six-month holding period

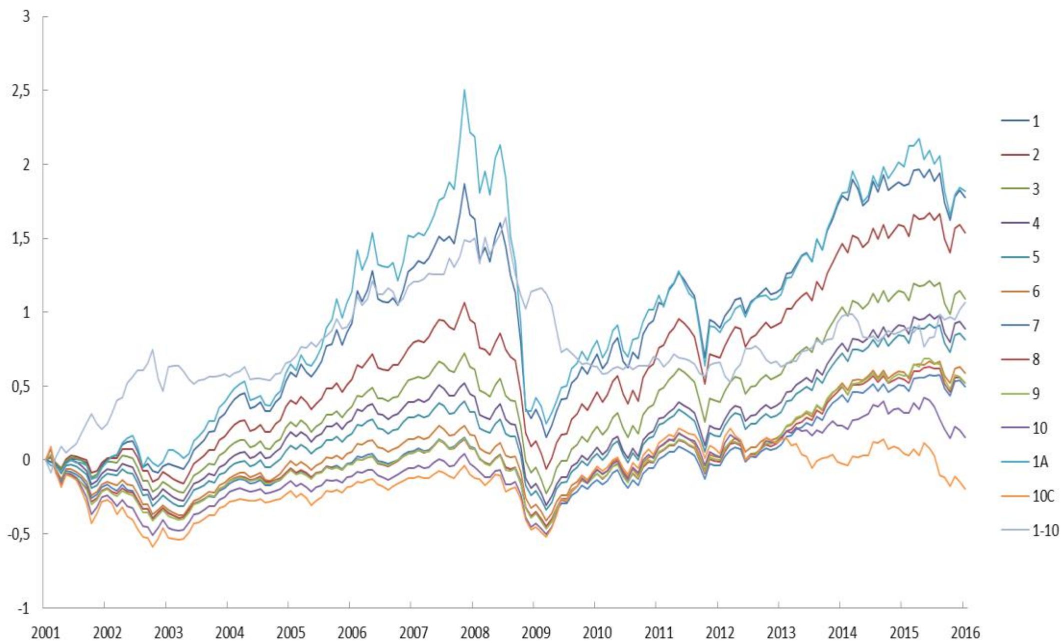
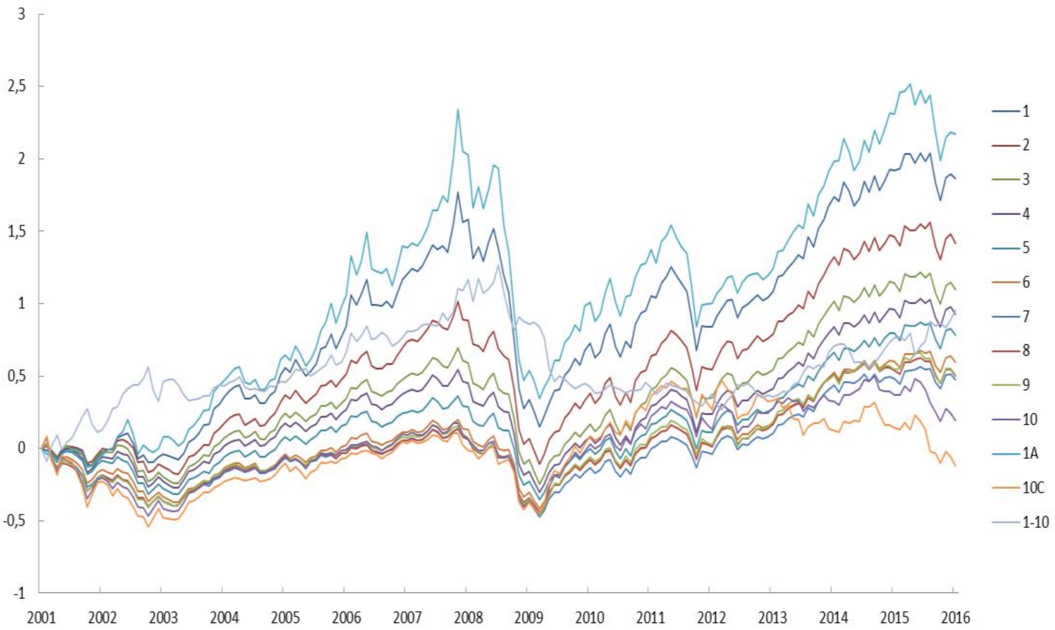


Figure 5: Cumulative returns on ranked portfolios with three-month holding period

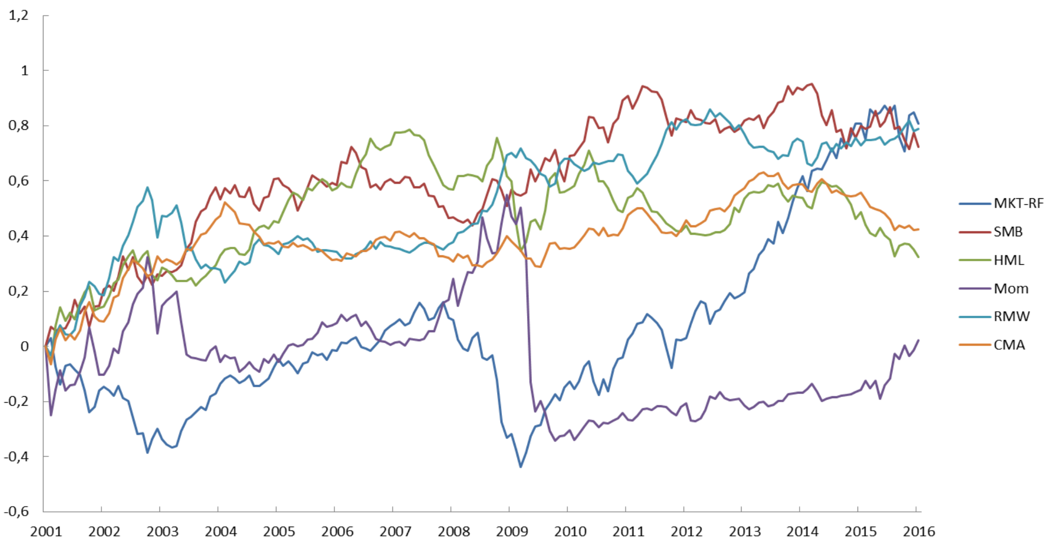


5.7.3 Regression Factors

The historical movements of the factors used in the regression models could provide important implications in the models used. Carhart (1997) argues that the momentum factor generates significant improvements in terms of explanatory power in variation of the cross-sectional returns compared to Fama and French 3-factor model. In addition, when Fama and French introduced the 5-factor model, they deliberately excluded the momentum factor. As this thesis uses both models, an evaluation of the different factors can therefore give us interesting implications.

From figure 6, we can observe that the momentum factor is affected by a much larger extent in the two crises we have in our sample, especially in the year after the great recession (recovery state) compared to the other risk factors, as they all show positive and fairly stable cumulative return.

Figure 6: Cumulative returns on regression factors



According to table 3, all factors exhibit positive return with MKT-RF holding the highest mean. The minimum returns shows that momentum was struck considerable more than the other risk factors with its lowest min. value and risk-return ratio (Mean/St.Dev) being -34,58% and 3,18%. The two additional factors, CMA and RMW both exhibit low maximum values and low standard deviations, but offer relatively high Mean/St.Dev ratio. Even though MOM generates the highest average return, it is evident that the financial crisis of 2008 had huge impact on it. It can be further shown that SMB, HML, RMW and CMA appear to be relative stable through the whole sample period.

Table 3: Descriptive statistics on regression factors

	Mean	St.Dev.	Mean/ St.Dev	Max	Min	Kurtosis	Skewness
MKT-RF	0,43 %	4,45 %	9,66 %	11,35 %	-17,23 %	1,0476	-0,5954
SMB	0,34 %	2,60 %	12,92 %	7,08 %	-6,54 %	-0,2035	0,1714
HML	0,19 %	2,70 %	7,11 %	13,91 %	-9,67 %	4,2142	0,3793
MOM	0,17 %	5,43 %	3,18 %	12,48 %	-34,58 %	11,3284	-2,1623
RMW	0,35 %	2,19 %	15,84 %	7,99 %	-8,86 %	2,9585	0,0466
CMA	0,21 %	1,90 %	11,29 %	9,51 %	-6,53 %	3,9112	0,8375

All numbers are based on monthly returns in the time period 2001:01 - 2015:12

As to table 4, multicollinearity does not appear to be of concern. The market excess return (MKT-RF) is negatively correlated with majority of the other risk factors used, which implies that the CAPM alone loses quite a bit of explanatory power in variations of cross-sectional returns. Both CMA and RMW show high positive correlation with HML, which is consistent to what Fama and French (2015) concluded. HML becomes redundant when these two new factors are included to describe average returns.

Table 4: Correlation matrix of regression factors

	MKT-RF	*SMB*	*HML*	*MOM*	*RMW*	*CMA*
MKT-RF	1	0,333087	-0,00881	-0,47055	-0,59643	-0,14113
SMB	0,333087	1	0,009505	-0,18607	-0,41182	-0,00588
HML	-0,00881	0,009505	1	0,057126	0,247008	0,578924
MOM	-0,47055	-0,18607	0,057126	1	0,479631	0,214743
RMW	-0,59643	-0,41182	0,247008	0,479631	1	0,149028
CMA	-0,14113	-0,00588	0,578924	0,214743	0,149028	1

All numbers are based on monthly returns in the time period 2001:01 - 2015:12

6 Results

This section starts off by a discussion of linear regression validity. Next in line, we will emphasize on the results obtained by our three different trading strategies and analyze them to check for persistence. The sorted portfolios will be presented in an ascending order based on the holding periods. All tables will report results estimated by CAPM, Carhart 4-factor model and Fama-French 5-factor model. Carhart 4-factor model is favored in risk adjustment processes in general, while the CAPM and Fama-French 5-factor model are for comparative reasons and further followed by a small discussion why Carhart 4-factor model is preferred when it comes to explaining risk-adjusted returns. Sharpe ratio is included to mainly act as an external analysis of performance between the three holding strategies. Results from market timing model are then presented, as it may contribute to mutual fund performance. Lastly, this section ends with post-formation returns on portfolios and contingency tables to see how yields and rankings have evolved throughout the sample period.

6.1 Diagnostic Tests

Since we are primarily working with cross-sectional time series, it is necessary to perform a linear regression validity test in order to avoid spurious regressions. This test involves the five classical OLS assumptions:

i. $E(u_t) = 0$
ii. $Var(u_t) = \sigma^2 < \infty$
iii. $Cov(u_t, u_j) = 0$
iv. $Cov(u_t, x_t) = 0$
v. $u_t \sim N(0, \sigma^2)$

The regressions require all five assumptions to hold in order to obtain valid estimations. However, the normality assumption is less restrictive compared to the rest when it comes to OLS regression to be best linear unbiased estimator (BLUE). A detailed walkthrough and explanation of each single assumption will simply add very little to zero economic intuition to our thesis objective, thus we have decided to skip an extensive elaboration on this part and moved the tables to the appendix section. In a short summary, we applied White and Breusch-Godfrey in order to detect for heteroscedasticity and serial correlations with Jarque-Bera for normality, which are presented in appendix section (table 13). All regressions that are subject to heteroscedasticity and serial correlations are corrected by following Newey-West (1987) procedures. Another important feature is that most of the regressions do not exhibit normality, and thus the standard t-test cannot be fully trusted. Unfortunately, there is also no obvious remedy to counter this problem. However, central limit theorem and law of large numbers state that, given certain conditions, the distribution of the sum of large sample size will be approximately normally distributed, regardless of the underlying distribution. As our sample size is assumed to be sufficiently large enough, thus the statistical inferences should be correct.

6.2 All Funds Equally Weighted

The purpose of this section is to study EW and convey insightful information that can be extracted from its statistics. Table 5 shows that EW yields a positive monthly excess return of 0,44% with a monthly standard deviation of 4,64%. This is somewhat very similar to the market proxy that exhibits monthly excess return and standard deviation of 0,43% and 4,45% (Table 1).

On the regressions, the risk-adjusted performance measure alpha is highly insignificant and can be seen in all three models (CAPM, Carhart 4-factor, Fama-French 5-factor). Thus, the equally weighted portfolio of all funds is unable to create abnormal returns. The market factor's beta is close to one, this is expected given that EW is characterized as a well-diversified portfolio. Furthermore, it also shows positive and significant exposure to small-cap and value stocks. A somewhat unexpected outcome is when RMW and CMA are introduced with the imperceptible increase in adjusted r-squared. Arguably, Carhart 4-factor model performs as well as the Fama-French 5-factor model in this case, supported by the results of RMW and CMA being insignificant, thus adding these factors serve no purpose and the increase of 0,0002% in adjusted R^2 (from 4-factor to 5-factor) could be an outcome of data mining.

Table 5: Equally weighted portfolio of all funds

CAPM										
	M. Excess Ret.	St.Dev.	SR	Alpha	MKT_RF	Adj. R^2				
All funds (EW)	0,44 %	4,64 %	9,40 %	-0,001 %	1,0175***	0,9523				
				(0,9892)	(0,0000)					
Carhart										
	M. Excess Ret.	St.Dev.	SR	Alpha	MKT_RF	HML	SMB	MOM	Adj. R^2	
All funds (EW)	0,44 %	4,64 %	9,40 %	-0,069 %	0,9953***	0,0705**	0,1788***	0,0214	0,9630	
				(0,3367)	(0,000)	(0,0333)	(0,0000)	(0,2576)		
Fama-French 5										
	M. Excess Ret.	St.Dev.	SR	Alpha	MKT_RF	HML	SMB	RMW	CMA	Adj. R^2
All funds (EW)	0,44 %	4,64 %	9,40 %	-0,063 %	0,9861***	0,0997**	0,1859***	0,0313	-0,0815	0,9632
				(0,3956)	(0,0000)	(0,0104)	(0,0000)	(0,4246)	(0,1364)	

This table displays regression results obtained by regressing an equally weighted portfolio of all mutual funds net of risk free rate and management fee against CAPM, 4-factor and 5-factor models. All numbers are based on monthly returns in the time period 2001:01 - 2015:12. MKT_RF, HML, SMB, RMW and CMA are Fama and French's market proxy and factor-mimicking portfolios for book-to-market, size, profitability and investment equity. MOM is a factor-mimicking portfolio formed monthly based on one year momentum. The p-values are in parenthisis. ***, ** and * indicate 1%, 5% and 10% level of significance, respectively.

6.3 Three-Month Holding Strategy

The funds in our sample are now ranked to their lagged one-year simple returns and constructed into ten equally weighted portfolios. Portfolio 1 consists of the top 10% last year performing funds, while portfolio 10 contains worst 10% last year performing funds. In addition, the top 1/30 (46 funds) forms portfolio 1A, and bottom 1/30 forms portfolio 10C. In terms of monthly excess returns seen in table 6, the previous top funds seem to outperform others with returns of 0,71% and 0,79%, while the previous bottom funds provide anomalously poor returns of 0,26% and 0,15%. This is emphasized by the spread between portfolio 1 and 10 with 45 basis points (self-financing portfolio) and 1A-10C spread of 64 basis points. The Sharpe ratio appears to be in same track as monthly excess return, which shows increasing ratio with portfolios rankings as top decile offers Sharpe ratio of 14,69% and bottom decile with only 4,60%.

The risk-adjusted alphas tell a similar story of increasing returns with ranking. However, most of the alphas are insignificant. It can be further seen that only portfolio 6 and 7 exhibit significant alphas at 5%-level estimated by Carhart 4-factor and Fama French 5-factor models, but they all offer negative alphas. In other words, if a portfolio has positive alpha, it is most likely insignificant, and if it has significant alpha, it is most likely negative, which is consistent with the findings from Carhart (1997) and Bollen and Busse (2005) in their study of persistence. This further indicates that there are some persistence within bad performers as they tend remain as bad performers over the next period.

All three models show a very similar explanatory power, but we are still able to draw some interesting differences between the models. The CAPM model manages to capture most of the variations of cross-sectional returns with an adjusted R^2 ranging from 60% to 97% among portfolios 1 to 10. Carhart 4-factor model is able to increase the explained variations from CAPM's estimations, due to significant exposures to size (SMB) and momentum (MOM) in most of the portfolios, while value (HML) only contributes in few of the sorted portfolios. To our surprise, the Fama and French 5-factor model achieves worse results than 4-factor in general. This could be an outcome from excluding momentum factor even though it has shown to be highly significant overall. Once again, HML also becomes redundant when profitability and investments factors have been added into the equation. However, Fama and French 5-factor model yield highest explanatory power when it comes to portfolios with significant alphas, which strikes us as an anomaly even though the increase is negligible. Another interesting remark is the exposure towards the one-year momentum effect. It appears that factor loading increases with portfolio ranking, as higher ranked portfolios entail higher exposure towards MOM. This implies that the top performing portfolios invest significantly more in momentum strategies. This can also be seen in Carhart (1997), his study of persistence in mutual fund performance.

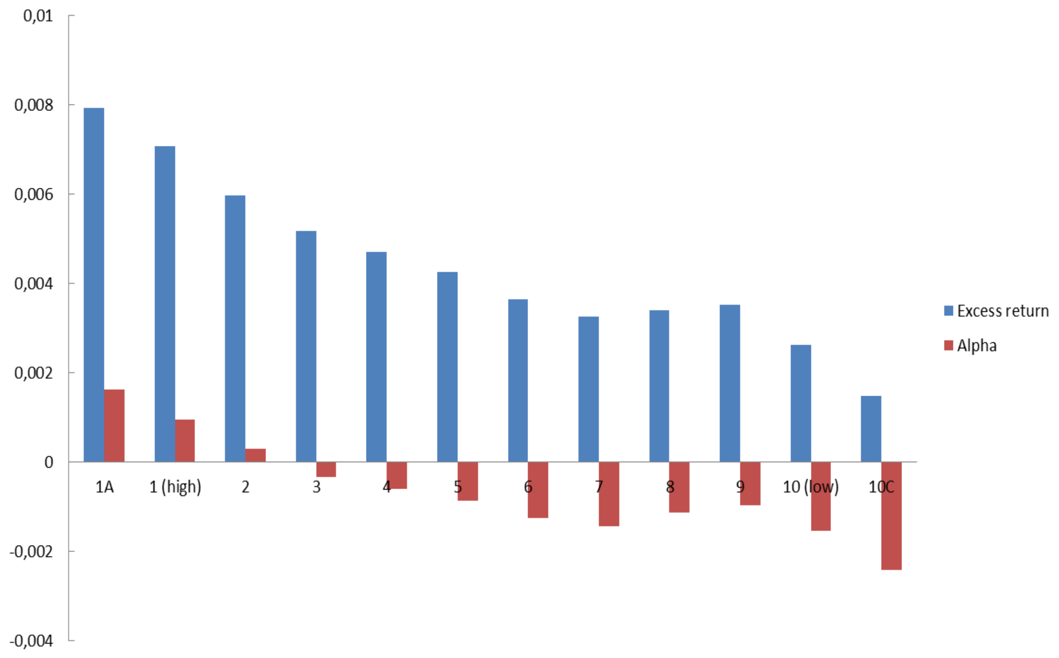
Table 6: Ranked portfolios based on one-year moving average of mutual funds and rebalanced every three months

					CAPM				Carhart							Fama-French 5			
Portfolio	Monthly excess return	Std dev	SR	Alpha	MKT-RF	Adj. R^2	Alpha	MKT-RF	HML	SMB	MOM	Adj. R^2	Alpha	MKT-RF	HML	SMB	RMW	CMA	Adj. R^2
1A	0,79 %	5,39 %	14,69 %	0,0034	0,9386***	0,5273	0,0010	1,0985***	0,1332	0,2505**	0,3620***	0,6287	0,0019	0,9325***	0,2213	0,2723**	0,2008	-0,2194	0,5405
				(0,2712)	(0,0000)		(0,7127)	(0,0000)	(0,2826)	(0,0170)	(0,0000)		(0,5553)	(0,0000)	(0,2504)	(0,0411)	(0,2418)	(0,3765)	
1 (high)	0,71 %	4,87 %	14,52 %	0,0028	0,9562***	0,7052	0,0008	1,0476***	0,1408	0,2830***	0,2539***	0,7845	0,0012	0,9432***	0,1804	0,3051***	0,1790*	-0,1176	0,7291
				(0,1826)	(0,0000)		(0,6562)	(0,0000)	(0,1043)	(0,0002)	(0,0000)		(0,5830)	(0,0000)	(0,1419)	(0,0011)	(0,0992)	(0,4529)	
2	0,60 %	4,55 %	13,12 %	0,0020	0,9643***	0,8856	0,0006	0,9902***	0,1603***	0,2444***	0,1277***	0,9297	0,0003	0,9597***	0,1197**	0,2630***	0,1435**	0,0637	0,9137
				(0,1870)	(0,0000)		(0,5053)	(0,0000)	(0,0018)	(0,0000)	(0,0000)		(0,7422)	(0,0000)	(0,0442)	(0,0000)	(0,0133)	(0,4033)	
3	0,52 %	4,56 %	11,35 %	0,0009	0,9898***	0,9203	-0,0003	0,9930***	0,1485***	0,2389***	0,0852***	0,9520	-0,0006	0,9816***	0,1215**	0,2607***	0,1383***	0,0214	0,9460
				(0,3698)	(0,0000)		(0,6657)	(0,0000)	(0,0010)	(0,0000)	(0,0045)		(0,4357)	(0,0000)	(0,0104)	(0,0000)	(0,0040)	(0,7260)	
4	0,47 %	4,55 %	10,33 %	0,0003	0,9974***	0,9418	-0,0006	0,9976***	0,1027**	0,2005***	0,0674***	0,9617	-0,0009	0,9892***	0,0869**	0,2195***	0,1160***	0,0000	0,9580
				(0,7188)	(0,0000)		(0,3304)	(0,0000)	(0,0129)	(0,0000)	(0,0006)		(0,2025)	(0,0000)	(0,0360)	(0,0000)	(0,0095)	(0,9994)	
5	0,43 %	4,53 %	9,39 %	0,0000	1,0034***	0,9523	-0,0007	0,9916***	0,0971***	0,1851***	0,0413*	0,9670	-0,0010	0,9911***	0,0858**	0,2009***	0,0908**	-0,0056	0,9660
				(0,9395)	(0,0000)		(0,2361)	(0,0000)	(0,0095)	(0,0000)	(0,0657)		(0,1262)	(0,0000)	(0,0222)	(0,0000)	(0,0244)	(0,9150)	
6	0,36 %	4,54 %	8,03 %	-0,0007	1,0105***	0,9645	-0,0013**	0,9883***	0,0563**	0,1704***	0,0186	0,9740	-0,0012**	0,9797***	0,0803**	0,1758***	0,0240	-0,0658	0,9741
				(0,2861)	(0,0000)		(0,0250)	(0,0000)	(0,0456)	(0,0000)	(0,3336)		(0,0364)	(0,0000)	(0,0150)	(0,0000)	(0,4552)	(0,1692)	
7	0,33 %	4,65 %	7,01 %	-0,0010*	1,0222***	0,9731	-0,0014**	0,9969***	0,0293	0,1187***	-0,0041	0,9770	-0,0013**	0,9946***	0,0719***	0,1240***	0,0095	-0,1108**	0,9783
				(0,0631)	(0,0000)		(0,0120)	(0,0000)	(0,1820)	(0,0000)	(0,8206)		(0,0178)	(0,0000)	(0,0089)	(0,0000)	(0,7413)	(0,0103)	
8	0,34 %	4,70 %	7,21 %	-0,0009	1,0229***	0,9604	-0,0011	0,9807***	0,0142	0,1082***	-0,0368*	0,9647	-0,0011	0,9983***	0,0511	0,1169***	0,0152	-0,1081*	0,9644
				(0,1710)	(0,0000)		(0,1102)	(0,0000)	(0,5936)	(0,0014)	(0,0701)		(0,1367)	(0,0000)	(0,1431)	(0,0020)	(0,7071)	(0,0557)	
9	0,35 %	4,96 %	7,10 %	-0,0010	1,0626***	0,9436	-0,0009	0,9890***	0,0232	0,1132***	-0,0899***	0,9544	-0,0007	1,0111***	0,0962**	0,1101***	-0,0692	-0,1697***	0,9493
				(0,2369)	(0,0000)		(0,2143)	(0,0000)	(0,4211)	(0,0005)	(0,0000)		(0,3863)	(0,0000)	(0,0156)	(0,0019)	(0,1807)	(0,0020)	
10 (low)	0,26 %	5,70 %	4,60 %	-0,0026*	1,1455***	0,8613	-0,0017	0,9776***	-0,0672	0,1251**	-0,2492***	0,9134	-0,0006	1,0122***	0,1032	0,0832	-0,3340***	-0,3224***	0,8804
				(0,0909)	(0,0000)		(0,1565)	(0,0000)	(0,1346)	(0,0119)	(0,0000)		(0,6641)	(0,0000)	(0,1324)	(0,1714)	(0,0002)	(0,0007)	
10C	0,15 %	6,60 %	2,23 %	-0,0044*	1,2129***	0,7204	-0,0029	0,9502***	-0,1445*	0,1826*	-0,3942***	0,8187	-0,0010	0,9956***	0,0949	0,1004	-0,5919***	-0,4044**	0,7563
				(0,0795)	(0,0000)		(0,1654)	(0,0000)	(0,0964)	(0,0633)	(0,0000)		(0,6874)	(0,0000)	(0,4510)	(0,4189)	(0,0000)	(0,0121)	
1-10 spread	0,45 %	3,81 %	11,67 %	0,0036	-0,1855**	0,0471	0,0007	0,0749	0,2026**	0,1554*	0,5044***	0,5333	0,0000	-0,0636	0,0684	0,2197*	0,5158***	0,2115	0,1279
				(0,1745)	(0,0236)		(0,6871)	(0,2662)	(0,0264)	(0,0520)	(0,0000)		(0,9848)	(0,4758)	(0,6516)	(0,0849)	(0,0001)	(0,2673)	
1A-10C spread	0,64 %	5,97 %	10,79 %	0,0060	-0,2705**	0,0396	0,0021	0,1532	0,2721*	0,0655	0,7576***	0,4687	0,0011	-0,0577	0,1177	0,1697	0,7954***	0,1917	0,0985
				(0,1623)	(0,0486)		(0,5113)	(0,2144)	(0,0703)	(0,6271)	(0,0000)		(0,7923)	(0,6987)	(0,6425)	(0,4043)	(0,0006)	(0,5553)	

This table displays regression results obtained by regressing equally weighted portfolios net of risk free rate and management fee against CAPM, 4-factor and 5-factor models. All numbers are based on monthly returns in the time period 2001:01 - 2015:12. Mutual funds are sorted into equally weighted portfolios based on their previous calendar year's return. Funds with highest past returns comprise portfolio 1, and funds with the lowest comprise portfolio 10.Portfolio 1A and 10C consist of the top 1/30 and bottom 1/30 on the same measure . MKT_RF, HML, SMB, RMW and CMA are Fama and French's market proxy and factor-mimicking portfolios for book-to-market, size, profitability and investment equity. MOM is a factor-mimicking portfolio formed monthly based on one year momentum. The p-values are in parenthisis. ***, ** and * indicate 1%, 5% and 10% level of significance, respectively.

The purpose of figure 7 is to display an enhanced picture of the patterns described above. Now we can clearly see that both excess returns and risk-adjusted alphas more or less increase with portfolio ranking. According to Efficient Market Hypothesis, the columns should have been evenly distributed. Even though there is some presence of anomalies, one should keep in mind that all alphas, except those in portfolio 6 and 7 (negative alphas) are not significant different from zero. Hence, market participants will most likely not be able to generate positive abnormal returns by following such strategy.

Figure 7: Monthly excess returns and risk-adjusted alphas of ranked portfolios in three-month strategy



6.4 Six-Month Holding Strategy

The process of portfolio sorting is the same as previous strategy, the main difference lies in the holding period, increased from three to six months. According to table 7, monthly excess returns are positive and still increasing with portfolio ranking. The pattern is almost identical to the three-month holding strategy, but the six-month strategy offers lower monthly excess return overall. This is most likely due to less frequent rebalancing. Thus, the top portfolios 1A and 1 decrease from 79 to 75 and 71 to 70 basis points between the strategies. There is also a marginal decrease in bottom portfolios, where portfolio 10 and 10C only yield 0,23% and 0,08% from 0,26% and 0,15% that was produced by the three-month holding strategy. As expected, six-month holding strategy offers lower Sharpe ratios in general.

The risk-adjusted alphas follow a similar trend. We can observe that the alphas are increasing along with the ranking of the portfolios, but none of them are significant except for portfolios 6 and 7 at 10% and 5% levels. Once again, portfolios with bad performance are the ones who are more likely to persist on underperforming.

As to model specification, there are no significant changes between the two strategies. Carhart 4-factor model still prevails in terms of explanatory power, except for portfolios that exhibit significant alphas as the 5-factor model somewhat yields higher adjusted R^2. Market proxies are all approximate equal to one and SMB shows presence of significances across the portfolios. In addition to the increasing exposure of MOM with portfolio rankings, it can be observed that portfolios with significant negative alphas (6 and 7) are not significantly exposed to MOM, at least within 5%-level. This implies that underperformed portfolios in terms of abnormal returns are less likely to have included momentum investments. This behavior can be seen in all three strategies.

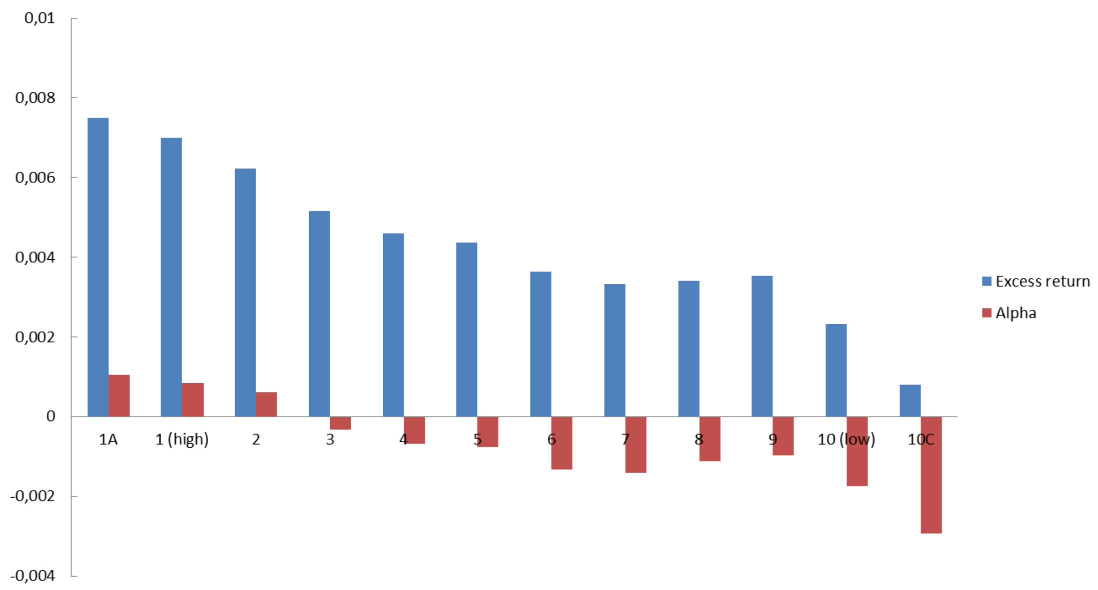
Table 7: Ranked portfolios based on one-year moving average of mutual funds and rebalanced every six months

				CAPM			Carhart						Fama-French 5						
Portfolio	Monthly excess return	Std dev	SR	Alpha	MKT-RF	Adj. R^2	Alpha	MKT-RF	HML	SMB	MOM	Adj. R^2	Alpha	MKT-RF	HML	SMB	RMW	CMA	Adj. R^2
1A	0,75 %	5,74 %	13,07 %	0,0030	0,9567***	0,6017	0,0007	1,0908***	0,2809***	0,0822	0,3280***	0,6959	0,0018	0,9218***	0,2726**	0,1193	-0,0377	0,0674	0,6104
				(0,2667)	(0,0000)		(0,7490)	(0,0000)	(0,0017)	(0,4433)	(0,0000)		(0,5156)	(0,0000)	(0,0222)	(0,3867)	(0,8444)	(0,6241)	
1 (high)	0,70 %	5,06 %	13,84 %	0,0026	0,9848***	0,7319	0,0006	1,0705***	0,2770***	0,1222	0,2419***	0,8020	0,0012	0,9581***	0,2796***	0,1339	-0,0110	0,0944	0,7492
				(0,2104)	(0,0000)		(0,7070)	(0,0000)	(0,0001)	(0,1468)	(0,0000)		(0,5603)	(0,0000)	(0,0020)	(0,2213)	(0,9385)	(0,359)	
2	0,62 %	4,56 %	13,68 %	0,0020	0,9835***	0,8726	0,0006	1,0095***	0,2565***	0,1298**	0,1309***	0,9132	0,0004	0,9726***	0,2753***	0,1079	0,0204	0,1392**	0,8966
				(0,1149)	(0,0000)		(0,5532)	(0,0000)	(0,0000)	(0,0273)	(0,0000)		(0,6962)	(0,0000)	(0,0000)	(0,1287)	(0,8159)	(0,0265)	
3	0,52 %	4,59 %	11,26 %	0,0010	1,0037***	0,9194	-0,0001	1,0044***	0,2369***	0,1407***	0,0802***	0,9481	-0,0004	0,9926***	0,2573***	0,1198**	0,0095	0,1288**	0,9428
				(0,3706)	(0,0000)		(0,8264)	(0,0000)	(0,0000)	(0,0035)	(0,0053)		(0,5858)	(0,0000)	(0,0000)	(0,0210)	(0,8825)	(0,0103)	
4	0,46 %	4,57 %	10,06 %	0,0002	1,0026***	0,9445	-0,0006	1,0074***	0,1732***	0,1049**	0,0660***	0,9613	-0,0009	1,0003***	0,1920***	0,0851**	0,0097	0,1158**	0,9579
				(0,7913)	(0,0000)		(0,3480)	(0,0000)	(0,0000)	(0,0117)	(0,0009)		(0,2088)	(0,0000)	(0,0000)	(0,0354)	(0,8517)	(0,0103)	
5	0,44 %	4,57 %	9,56 %	0,0000	1,0117***	0,9542	-0,0007	1,0016***	0,1708***	0,0961**	0,0395*	0,9670	-0,0010	1,0059***	0,1892***	0,0784**	0,0032	0,1036***	0,9664
				(0,927)	(0,0000)		(0,2832)	(0,0000)	(0,0000)	(0,0123)	(0,0757)		(0,1171)	(0,0000)	(0,0000)	(0,0322)	(0,9457)	(0,0079)	
6	0,36 %	4,58 %	7,94 %	-0,0004	1,0053***	0,9681	-0,0009*	0,9822***	0,1561***	0,0517*	0,0122	0,9760	-0,0010*	0,9847***	0,1670***	0,0645**	-0,0529	0,0502	0,9764
				(0,5035)	(0,0000)		(0,0820)	(0,0000)	(0,0000)	(0,0533)	(0,5173)		(0,0537)	(0,0000)	(0,0000)	(0,0255)	(0,2398)	(0,1151)	
7	0,33 %	4,61 %	7,21 %	-0,0010**	1,0177***	0,9759	-0,0014***	0,9879***	0,1226***	0,0341*	-0,0106	0,9805	-0,0013***	0,9914***	0,1269***	0,0598**	-0,0698*	0,0079	0,9808
				(0,0428)	(0,0000)		(0,0058)	(0,0000)	(0,0000)	(0,0966)	(0,5455)		(0,0076)	(0,0000)	(0,0000)	(0,0229)	(0,0784)	(0,7689)	
8	0,34 %	4,64 %	7,36 %	-0,0015	1,0051***	0,9571	-0,0016	0,9607***	0,1153***	0,0203	-0,0383*	0,9622	-0,0017	0,9812***	0,1279***	0,0646*	-0,1338**	0,0297	0,9626
				(0,1348)	(0,0000)		(0,1175)	(0,0000)	(0,0012)	(0,4817)	(0,0749)		(0,1119)	(0,0000)	(0,0009)	(0,0803)	(0,0123)	(0,4908)	
9	0,35 %	4,87 %	7,27 %	-0,0011	1,0424***	0,9374	-0,0011	0,9737***	0,1063***	0,0393	-0,0839***	0,9472	-0,0009	0,9964***	0,1088**	0,1219***	-0,2038***	-0,0447	0,9440
				(0,1925)	(0,0000)		(0,1831)	(0,0000)	(0,0072)	(0,2237)	(0,0006)		(0,285)	(0,0000)	(0,0152)	(0,0044)	(0,0012)	(0,4207)	
10 (low)	0,23 %	5,49 %	4,23 %	-0,0020	1,1179***	0,8518	-0,0014	0,9555***	0,1727***	-0,0338	-0,2236***	0,8980	-0,0002	0,9774***	0,1354*	0,1610**	-0,3864***	-0,3118***	0,8756
				(0,1907)	(0,0000)		(0,292)	(0,0000)	(0,0036)	(0,4939)	(0,0000)		(0,8553)	(0,0000)	(0,0600)	(0,0314)	(0,0000)	(0,0000)	
10C	0,08 %	6,35 %	1,26 %	-0,0043*	1,1908***	0,7023	-0,0034	0,9498***	0,2261**	-0,0129	-0,3428***	0,7762	-0,0012	0,9632***	0,1502	0,2902**	-0,5609***	-0,5651***	0,7411
				(0,0956)	(0,0000)		(0,1455)	(0,0000)	(0,0195)	(0,8819)	(0,0000)		(0,6323)	(0,0000)	(0,1880)	(0,0254)	(0,0002)	(0,0000)	
1-10 spread	0,47 %	3,62 %	12,94 %	0,0028	-0,1293*	0,0225	0,0003	0,1199*	0,1018	0,1505	0,4670***	0,4639	-0,0002	-0,0139	0,1420	-0,0357	0,3822**	0,4090***	0,0874
				(0,2772)	(0,0988)		-0,8547	(0,0672)	(0,1909)	(0,1083)	(0,0000)		(0,9203)	(0,8725)	(0,2405)	(0,7940)	(0,0230)	(0,0009)	
1A-10C spread	0,67 %	5,68 %	11,79 %	0,0055	-0,2303**	0,0342	0,0023	0,1459	0,0522	0,0897	0,6721***	0,4235	0,0013	-0,0360	0,1203	-0,1795	0,5299	0,6353***	0,0778
				(0,1533)	(0,0275)		(0,4263)	(0,1097)	(0,6693)	(0,5174)	(0,0000)		(0,7444)	(0,7874)	(0,5102)	(0,4672)	(0,1152)	(0,0007)	

This table displays regression results obtained by regressing equally weighted portfolios net of risk free rate and management fee against CAPM, 4-factor and 5-factor models. All numbers are based on monthly returns in the time period 2001:01 - 2015:12. Mutual funds are sorted into equally weighted portfolios based on their previous calendar year's return. Funds with highest past returns comprise portfolio 1, and funds with the lowest comprise portfolio 10.Portfolio 1A and 10C consist of the top 1/30 and bottom 1/30 on the same measure . MKT_RF, HML, SMB, RMW and CMA are Fama and French's market proxy and factor-mimicking portfolios for book-to-market, size, profitability and investment equity. MOM is a factor-mimicking portfolio formed monthly based on one year momentum. The p-values are in parenthisis. ***, ** and * indicate 1%, 5% and 10% level of significance, respectively.

As illustrated by Figure 8, the shape is exactly the same as the previous one. There are marginal differences in excess return that resulted to small decrease in the 1-10 spread. The findings in this strategy follow the same structure as the previous one.

Figure 8: Monthly excess returns and risk-adjusted alphas of ranked portfolios in six-month strategy



6.5 Twelve-Month Holding Strategy

The following strategy follows the same holding period applied in Carhart (1997) and the findings do not differentiate much from the previous strategies. Table 8 shows that monthly excess return is still increasing with portfolio ranking, but the current strategy offers the lowest monthly excess return compared to the more frequent rebalancing strategies. Naturally, this also applies to Sharpe ratios, as top performing portfolios 1A & 1 drop from 14,69% and 15,52% (three-month) to 13,03% and 13,43% (twelve-month). This suggests that less frequent rebalancing yields worse risk-adjusted returns, at least within the top performing portfolios.

The risk-adjusted alphas yet again could not find significant persistence except for portfolio 6 & 7 at 5% level. Carhart 4-factor model still achieves better results in general. It can be further seen that SMB and HML have swapped their places in terms of significance as SMB is now shown to be highly significant and HML only contributes in a handful of the portfolios. Thus, twelve-month holding strategy is significantly more exposed to SMB. MOM is still highly significant and displays a declining exposure along with decrease in ranking, same as the other holding strategies. Overall, the results point to more or less same patterns described earlier regarding persistence.

At last, there is a small trend observed in all three holding strategies that is not captured by the alphas; funds with high past simple returns yield higher excess returns and Sharpe ratios the next period compared to the other funds with low past simple returns. This is reflected by the fact that all three holding strategies exhibit the structure of ascending monthly excess returns and Sharpe ratios with portfolio rankings.

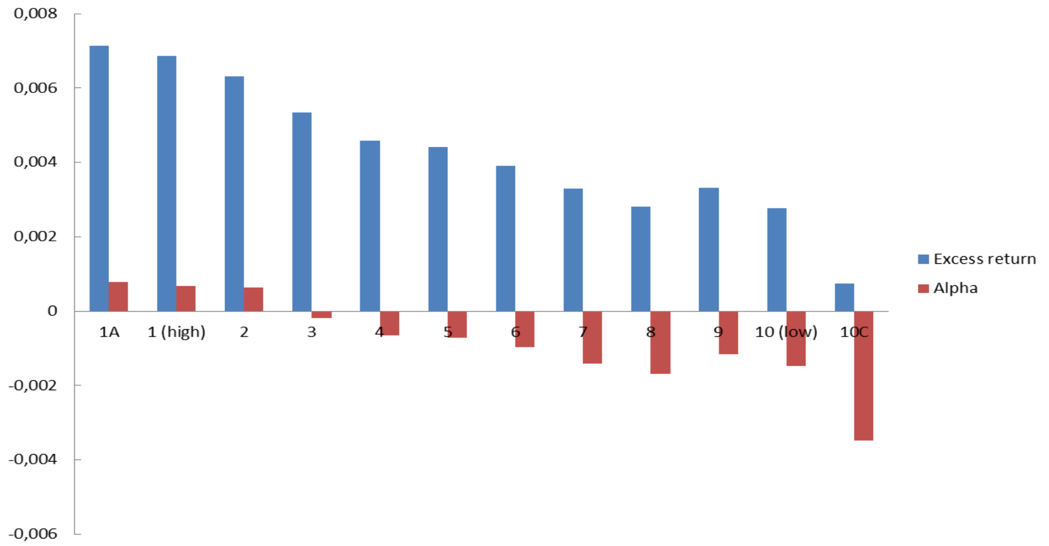
Table 8: Ranked portfolios based on one-year moving average of mutual funds and rebalanced every twelve months

				CAPM			Carhart						Fama-French 5						
Portfolio	Monthly excess return	Std dev	SR	Alpha	MKT-RF	Adj. R^2	Alpha	MKT-RF	HML	SMB	MOM	Adj. R^2	Alpha	MKT-RF	HML	SMB	RMW	CMA	Adj. R^2
1A	0,71 %	5,48 %	13,03 %	0,0043	0,8483***	0,4880	0,0016	1,0188***	0,1514	0,2822**	0,3913***	0,6262	0,0026	0,8377***	0,2260	0,2994**	0,1943	-0,1753	0,5067
				(0,1548)	(0,0000)		(0,5575)	(0,0000)	(0,2169)	(0,0141)	(0,0000)		(0,4021)	(0,0000)	(0,2464)	(0,0345)	(0,2032)	(0,5064)	
1 (high)	0,69 %	5,12 %	13,43 %	0,0031	0,9176***	0,7007	0,0009	1,0138***	0,1576**	0,2986***	0,2673***	0,7976	0,0014	0,8988***	0,1929**	0,3154***	0,1611	-0,0951	0,7298
				(0,1187)	(0,0000)		(0,5695)	(0,0000)	(0,0102)	(0,0000)	(0,0000)		(0,4804)	(0,0000)	(0,0356)	(0,0001)	(0,1776)	(0,4465)	
2	0,63 %	4,68 %	13,50 %	0,0019	0,9578***	0,8770	0,0003	0,9854***	0,1738***	0,2594***	0,1344***	0,9271	0,0002	0,9441***	0,1448**	0,2737***	0,1226**	0,0470	0,9081
				(0,1425)	(0,0000)		(0,7612)	(0,0000)	(0,0007)	(0,0000)	(0,0000)		(0,8697)	(0,0000)	(0,0222)	(0,0000)	(0,0396)	(0,5569)	
3	0,53 %	4,66 %	11,47 %	0,0009	0,9852***	0,9232	-0,0003	1,0005***	0,1414***	0,2267***	0,1022***	0,9565	-0,0006	0,9774***	0,1144**	0,2447***	0,1270***	0,0314	0,9465
				(0,3469)	(0,0000)		(0,6503)	(0,0000)	(0,0011)	(0,0000)	(0,0000)		(0,5061)	(0,0000)	(0,0204)	(0,0000)	(0,0087)	(0,6075)	
4	0,46 %	4,59 %	9,97 %	0,0004	0,9925***	0,9410	-0,0006	0,9921***	0,1024**	0,2148***	0,0712***	0,9633	-0,0008	0,9788***	0,0841**	0,2302***	0,1018**	0,0141	0,9587
				(0,6164)	(0,0000)		(0,3774)	(0,0000)	(0,0127)	(0,0000)	(0,0009)		(0,2743)	(0,0000)	(0,0469)	(0,0000)	(0,0195)	(0,7921)	
5	0,44 %	4,61 %	9,59 %	0,0000	0,9966***	0,9558	-0,0009	0,9954***	0,0813**	0,1765***	0,0571***	0,9706	-0,0011*	0,9884***	0,0615	0,1913***	0,0942**	0,0179	0,9678
				(0,9718)	(0,0000)		(0,1521)	(0,0000)	(0,0255)	(0,0000)	(0,0021)		(0,0890)	(0,0000)	(0,1001)	(0,0000)	(0,012)	(0,7314)	
6	0,39 %	4,54 %	8,59 %	-0,0007	1,0038***	0,9676	-0,0012**	0,9912***	0,0410	0,1505***	0,0286*	0,9753	-0,0013**	0,9866***	0,0491	0,1609***	0,05527*	-0,0393	0,9778
				(0,2877)	(0,0000)		(0,0276)	(0,0000)	(0,1414)	(0,0000)	(0,0904)		(0,0223)	(0,0000)	(0,144)	(0,0000)	(0,0928)	(0,4116)	
7	0,33 %	4,58 %	7,19 %	-0,0012	1,0303***	0,9705	-0,0014**	1,0000***	0,0380	0,1057***	-0,0171	0,9741	-0,0013**	1,0048***	0,0796**	0,1118***	0,0088	-0,1112**	0,9750
				(0,0549)	(0,0000)		(0,0169)	(0,0000)	(0,1327)	(0,0000)	(0,4516)		(0,0152)	(0,0000)	(0,0124)	(0,0001)	(0,7762)	(0,0114)	
8	0,28 %	4,57 %	6,15 %	-0,0011	1,0350***	0,9582	-0,0011	0,9891***	0,0077	0,1001***	-0,0459**	0,9626	-0,0012	1,0102***	0,0504	0,1094***	0,0128	-0,1235**	0,9619
				(0,1481)	(0,0000)		(0,1223)	(0,0000)	(0,7767)	(0,0036)	(0,0344)		(0,1014)	(0,0000)	(0,1814)	(0,0037)	(0,7604)	(0,0348)	
9	0,33 %	4,79 %	6,93 %	-0,0011	1,0781***	0,9331	-0,0010	1,0039***	0,0134	0,0957***	-0,0969***	0,9434	-0,0008	1,0297***	0,0905**	0,0940**	-0,0662	-0,1831***	0,9376
				(0,2505)	(0,0000)		(0,2795)	(0,0000)	(0,6822)	(0,0086)	(0,0000)		(0,4366)	(0,0000)	(0,0439)	(0,0186)	(0,2572)	(0,0031)	
10 (low)	0,28 %	5,39 %	5,13 %	-0,0024	1,1780***	0,8442	-0,0015	0,9819***	-0,0514	0,1595***	-0,2867***	0,9082	-0,0007	1,0419***	0,1297*	0,1278*	-0,3042***	-0,3732***	0,8640
				(0,1493)	(0,0000)		(0,2406)	(0,0000)	(0,2839)	(0,0028)	(0,0000)		(0,6851)	(0,0000)	(0,0881)	(0,0586)	(0,0024)	(0,0004)	
10C	0,07 %	6,31 %	1,18 %	-0,0039	1,2475***	0,7052	-0,0024	0,9347***	-0,1019	0,2540***	-0,4575***	0,8277	-0,0012	1,0392***	0,1481	0,2035*	-0,4730***	-0,5055***	0,7383
				(0,1494)	(0,0000)		(0,2473)	(0,0000)	(0,1812)	(0,0027)	(0,0000)		(0,6464)	(0,0000)	(0,2244)	(0,0609)	(0,0033)	(0,0027)	
1-10 spread	0,41 %	3,45 %	11,91 %	0,0038	-0,2566***	0,0850	0,0007	0,0368	0,2035***	0,1366	0,5554***	0,6074	0,0003	-0,1377*	0,0545	0,1854*	0,4680***	0,2848	0,1524
				(0,1691)	(0,0000)		(0,7024)	(0,4378)	(0,0024)	(0,0618)	(0,0000)		(0,9178)	(0,0734)	(0,6658)	(0,0992)	(0,0050)	(0,1005)	
1A-10C spread	0,64 %	5,15 %	12,42 %	0,0063	-0,3954***	0,0819	0,0022	0,0890	0,2478	0,0257	0,8501***	0,5653	0,0020	-0,1961	0,0691	0,0937	0,6701**	0,3369	0,1226
				(0,1396)	(0,0000)		(0,4542)	(0,2554)	(0,0241)	(0,8304)	(0,0000)		(0,6537)	(0,1097)	(0,7311)	(0,6001)	(0,0116)	(0,2224)	

This table displays regression results obtained by regressing equally weighted portfolios net of risk free rate and management fee against CAPM, 4-factor and 5-factor models. All numbers are based on monthly returns in the time period 2001:01 - 2015:12. Mutual funds are sorted into equally weighted portfolios based on their previous calendar year's return. Funds with highest past returns comprise portfolio 1, and funds with the lowest comprise portfolio 10.Portfolio 1A and 10C consist of the top 1/30 and bottom 1/30 on the same measure . MKT_RF, HML, SMB, RMW and CMA are Fama and French's market proxy and factor-mimicking portfolios for book-to-market, size, profitability and investment equity. MOM is a factor-mimicking portfolio formed monthly based on one year momentum. The p-values are in parenthisis. ***, ** and * indicate 1%, 5% and 10% level of significance, respectively.

As shown in figure 9, the histogram exhibits same distribution found in the previous strategies. In other words, the results are consistent with the findings by Carhart (1997) and none of the strategies are able to outperform the market.

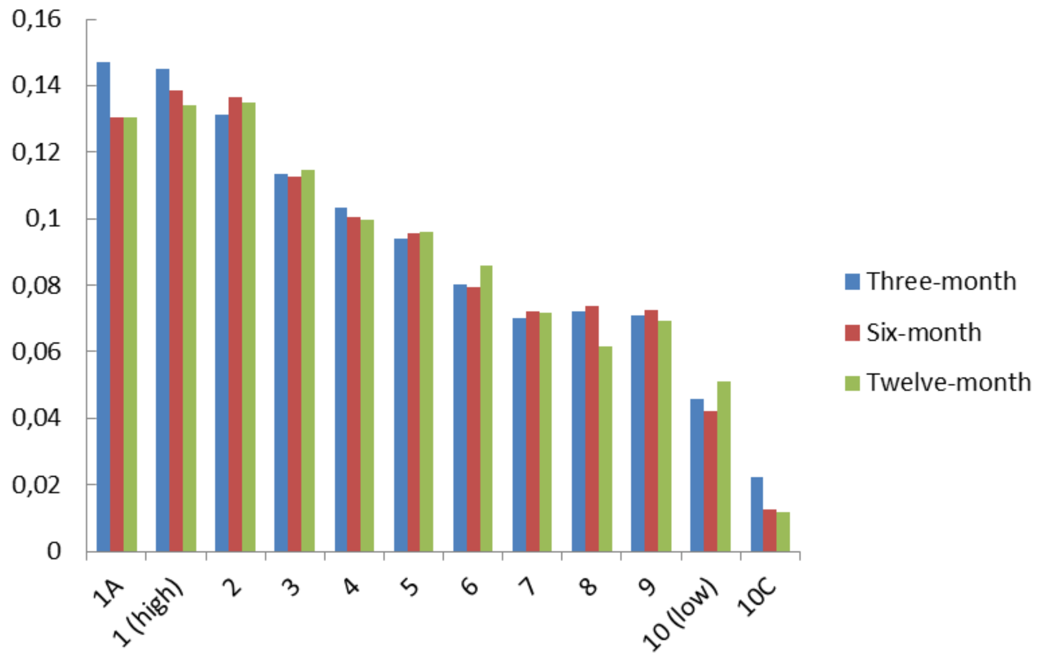
Figure 9: Monthly excess returns and risk-adjusted alphas of ranked portfolios in twelve-month holding strategy



6.6 Sharpe Ratio Comparisons

The purpose of figure 10 is to illustrate the results found above by the alternate measure of performance between the three holding strategies. In highest ranked portfolios (1A & 1), three-month holding strategy excels in terms of reward to variability, but loses its superiority in lower ranked portfolios except for 10C. As to six-month and twelve month holding strategies, it seems that six-month offers higher Sharpe ratios in general. Most interesting observation is that six-month and twelve-month yield higher Sharpe ratio than the three-month in the portfolios with significant negative alphas, namely 6 and 7. The three strategies share one common factor, which is Sharpe ratio increases with portfolio ranking. Nonetheless, Sharpe ratio itself does not provide evidence of persistence in performance and in our analysis only serves as a comparison tool between the portfolios in terms of risk-adjusted returns.

Figure 10: Sharpe ratio comparisons between the three holding strategies



6.6 Market Timing Results

If mutual fund managers were to possess market timing abilities, it would be a sign of outperformance. Therefore, in addition to testing whether or not fund managers have superior stock picking skills, we conduct a test for market timing. The three different holding periods are tested separately using CAPM, Carhart 4-factor and the Fama and French 5-factor model.

Similar to our previous tests, the Carhart 4-factor model performs better than CAPM and the 5-factor model. According to table 9, the top portfolio 1 and the sub-portfolio 1A both have negative market timing, with the quarterly holding period being less significant -0,0680 compared to the annual of -0,1221. As to the remaining portfolios, there are instances where there are signs of positive market timing in the annual strategy and semi-annual strategy, but it disappears in the quarterly holding period. However, none of the coefficients are significant, implying that none of the portfolios exhibit market timing ability for the different strategies.

Table 9: Henrikkson Merton market timing in Carhart 4-factor model

Market timing, Henrikkson Merton			
		Carhart	
	Twelve-month	Six-month	Three-month
Portfolio	β2	β2	β2
1A	-0,1221	-0,1123	-0,0680
	(0,6007)	(0,7158)	(0,7067)
1	-0,0695	-0,0324	-0,0715
	(0,7024)	(0,8635)	(0,5521)
2	0,0368	0,0734	-0,0144
	(0,7360)	(0,3827)	(0,8655)
3	0,0364	0,0398	-0,0143
	(0,6563)	(0,5763)	(0,8269)
4	0,0039	-0,0081	-0,0171
	(0,9503)	(0,9022)	(0,7845)
5	0,0097	-0,0155	-0,0037
	(0,8767)	(0,8032)	(0,944)
6	0,0065	-0,0350	-0,0127
	(0,8889)	(0,5061)	(0,8024)
7	0,0110	-0,0081	0,0145
	(0,7733)	(0,8664)	(0,8232)
8	-0,0298	-0,0660	-0,0177
	(0,5521)	(0,2596)	(0,7797)
9	-0,0696	-0,0757	-0,0506
	(0,2483)	(0,1836)	(0,4342)
10	-0,1038	-0,0409	0,0191
	(0,2711)	(0,6446)	(0,8407)
10C	-0,1418	0,0557	0,1476
	(0,4205)	(0,6893)	(0,3261)

This table displays regressions results obtained by regressing equally weighted portfolios net of risk free rate and management fee against CAPM, 4-factor and 5-factor models with inclusion of the Henriksson-Merton (HM) market timing factor. All numbers are based on monthly returns in the time period 2001:01 – 2015:12. Mutual funds are sorted into ten equally weighted portfolios based on their previous calendar year's return. Funds with highest past returns comprise portfolio 1, and funds with the lowest comprise portfolio 10. Portfolio 1A and 10C consist of the top thirtieth and bottom thirtieth on the same measure. The HM is a dummy variable that equals 1 if the market is greater than the risk-free rate and zero otherwise. The p-values are in parenthesis. ***, ** and * indicate 1%, 5% and 10% level of significance, respectively.

The results from the other two models are analogous, with some small differences seen in table 10. In both CAPM and the 5-factor model there are significant β2 in the 10C portfolio, whereas 5-factor model differentiate itself by capturing significant β2 in portfolio 10. Since we already found that the Carhart 4-factor model is considered as superior in our sample, the regression results seem to indicate that momentum disguises itself as timing ability in the models that do not include the momentum factor. Thus, Carhart 4-factor model reveals no signs of market timing abilities in the mutual fund industry in any of the three strategies, and if there are signs of market timing it does not seem to be in monthly data, same as the conclusions of Bollen and Bussen (2005).

Table 10: Henrikkson Merton market timing in CAPM and Fama-French 5-factor model

Market timing, Henrikkson Merton						
	CAPM			Fama-French 5-factor		
	Twelve-month	Six-month	Three-month	Twelve-month	Six-month	Three-month
Portfolio	β2	β2	β2	β2	β2	β2
1A	-0,3063	-0,2960	-0,3216	-0,3105	-0,2825	-0,2647
	(0.2280)	(0.1546)	(0.3215)	(0.2188)	(0.3666)	(0.1419)
1	-0,2097	-0,2287	-0,1820	-0,2137	-0,1607	-0,2131
	(0.3040)	(0.1114)	(0.3893)	(0.2758)	(0.4167)	(0.1275)
2	-0,0442	-0,0997	-0,0097	-0,0491	-0,0202	-0,1090
	(0.7341)	(0.3727)	(0.9290)	(0.6596)	(0.7854)	(0.2137)
3	-0,0170	-0,0792	-0,0172	-0,0168	-0,0194	-0,0864
	(0.8702)	(0.3782)	(0.8568)	(0.8344)	(0.7826)	(0.1904)
4	-0,0389	-0,0610	-0,0505	-0,0411	-0,0519	-0,0661
	(0.6106)	(0.4489)	(0.5388)	(0.5009)	(0.4218)	(0.2757)
5	-0,0174	-0,0390	-0,0426	-0,0177	-0,0418	-0,0448
	(0.8180)	(0.5581)	(0.5810)	(0.7722)	(0.4834)	(0.3673)
6	-0,0014	-0,0286	-0,0454	0,0101	-0,0320	-0,0224
	(0.9804)	(0.6277)	(0.4773)	(0.8268)	(0.5406)	(0.6389)
7	0,0168	0,0232	-0,0052	0,0336	0,0199	0,0507
	(0.7249)	(0.7547)	(0.9265)	(0.4276)	(0.6915)	(0.4652)
8	-0,0060	0,0109	-0,0416	0,0226	-0,0207	0,0376
	(0.9220)	(0.8342)	(0.4054)	(0.6870)	(0.7458)	(0.5770)
9	-0,0204	0,0074	-0,0213	0,0279	0,0180	0,0507
	(0.7528)	(0.9151)	(0.7333)	(0.6571)	(0.7663)	(0.4605)
10	0,0344	0,1910	0,1118	0,1273	0,1920*	0,2860**
	(0.7588)	(0.1156)	(0.3114)	(0.2253)	(0.0665)	(0.0132)
10C	0,0651	0,4201**	0,2967*	0,2082	0,4037**	0,5541**
	(0.7270)	(0.0292)	(0.0962)	(0.3073)	(0.0204)	(0.0027)

This table displays regressions results obtained by regressing equally weighted portfolios net of risk free rate and management fee against CAPM, 4-factor and 5-factor models with inclusion of the Henriksson-Merton (HM) market timing factor. All numbers are based on monthly returns in the time period 2001:01 – 2015:12. Mutual funds are sorted into ten equally weighted portfolios based on their previous calendar year's return. Funds with highest past returns comprise portfolio 1, and funds with the lowest comprise portfolio 10. Portfolio 1A and 10C consist of the top thirtieth and bottom thirtieth on the same measure. The HM is a dummy variable that equals 1 if the market is greater than the risk-free rate and zero otherwise. The p-values are in parenthesis. ***, ** and * indicate 1%, 5% and 10% level of significance, respectively.

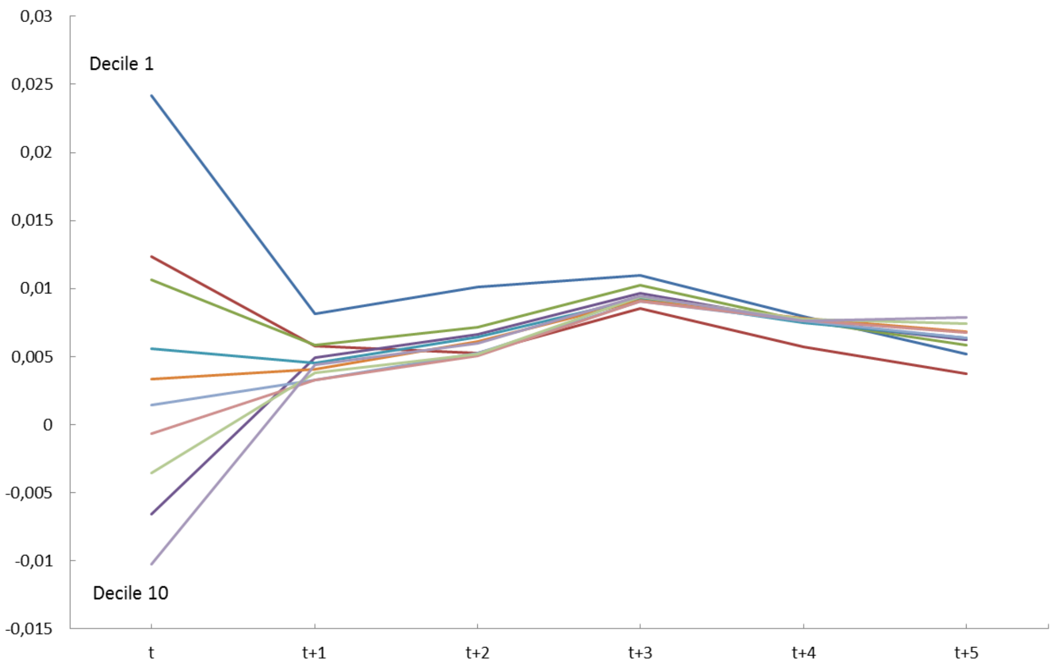
6.7 Post-Formation Returns on Ranked Mutual Fund Portfolios

In this section, we will present figure 11 that describes how each of the ranked portfolios perform in the years following their formation year. Thus, each line represents the average return of each portfolios five years post formation throughout the whole sample period. Naturally, there is no rebalancing in this test.

As one can observe from figure 10, decile 1 declines pretty steep from the formation year, *t* to the year after, *t+1*, this suggests that the high returns on the funds in the top portfolio are short-lived. The worst portfolio is on the other hand improving already from *t* to *t+1*.

After the first year, the portfolios across do not statistically differ from each other, which would imply no persistence. In the third year after formation, decile 1 is still above the rest by a small margin, however by the fifth it becomes the second worst. In economic sense, the returns of the portfolios appear to be quite random in the following years when no rebalancing is executed, proving that stocks do follow random walks to some extent. These findings are more or less equal on all three strategies with only minor insignificant differences. Additional figure is located in the appendix.

Figure 11: Post-formation returns on ranked portfolios based on twelve-month moving average



Each year from 2001:01 to 2015:12, funds are ranked into equal-weight portfolios based on the one-year previous simple return. The lines in the graph represent the excess return on each portfolio in the year prior to the initial year, and in each of the next five years post formation. Decile 1 consists of the funds with the highest formation year returns and funds with the lowest comprise decile 10.

6.8 Consistency in Ranking

For each of the three holding strategies, contingency tables of initial and subsequent twelve months mutual fund rankings are constructed. The columns reflect the probability of probability of being in portfolio rank *j* in the next period, after initial portfolio rank *i*.

With the three-month holding period (figure 12), the pairs [1,1] and [10,10] both have probabilities close to 60%. In general, this indicates that the top portfolio and bottom portfolio has a quite high probability of continuing that in the next quarter.

The table also shows that three-month holding period has very low probabilities that top (bottom) performing funds will end up at the bottom (top) in the subsequent quarter.

The six-month holding strategy is more evenly distributed (figure 13). The columns [1,1] and [10,10] still give the highest probabilities but not by the same amount as with the three-month strategy. It is also evident that the top (bottom) performers now have a higher chance of being bottom (top) in the subsequent period. The distribution of the portfolios ranging from two to nine seems somewhat arbitrary with the loser portfolios having a somewhat higher probability of remaining in the lower deciles.

In twelve-month holding period (figure 14), the distribution has balanced out more, although it is very similar to the six-month holding period. It is still quite clear that winners are more likely to continue as winners and losers are more likely to remain losers. However, the funds in the top decile change considerably each year with approximately 75% annual turnover in composition. The ranks of approximately 25% of the top and bottom funds seem to persist, but the year-to-year rankings on most mutual funds in the sample appear largely random.

Figure 12: Contingency table of the three-month holding strategy

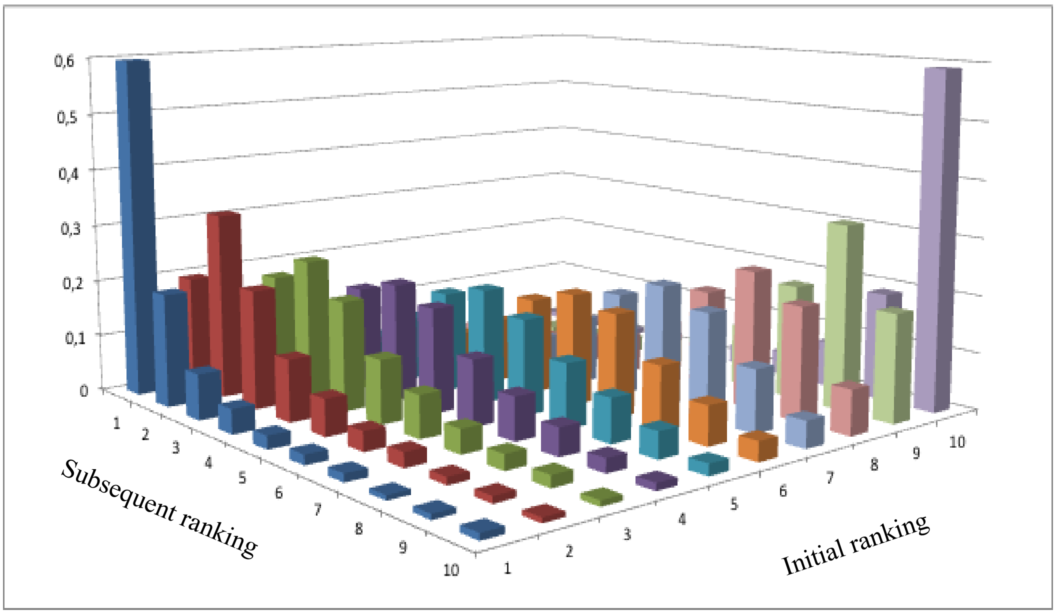


Figure 13: Contingency table of the six-month holding strategy

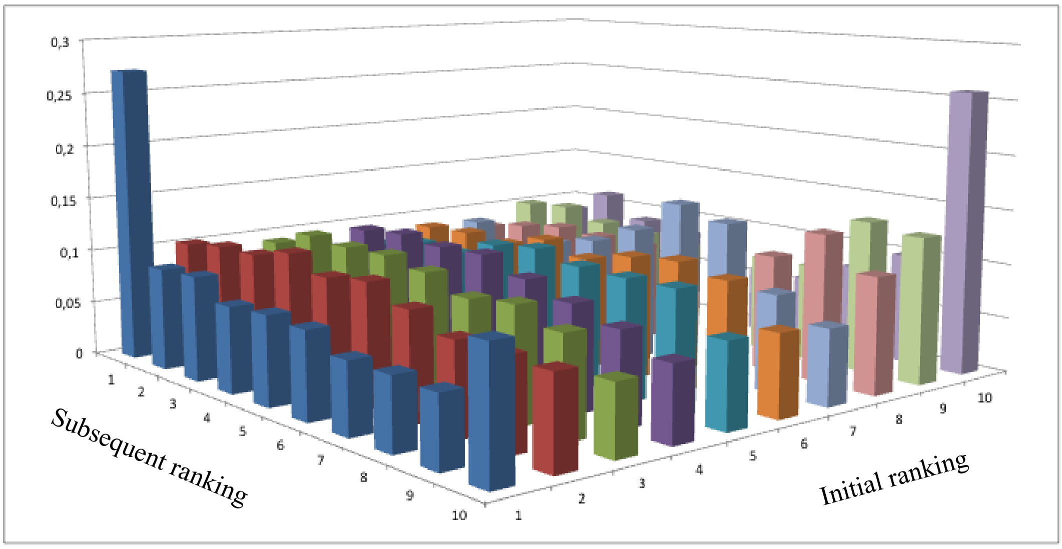
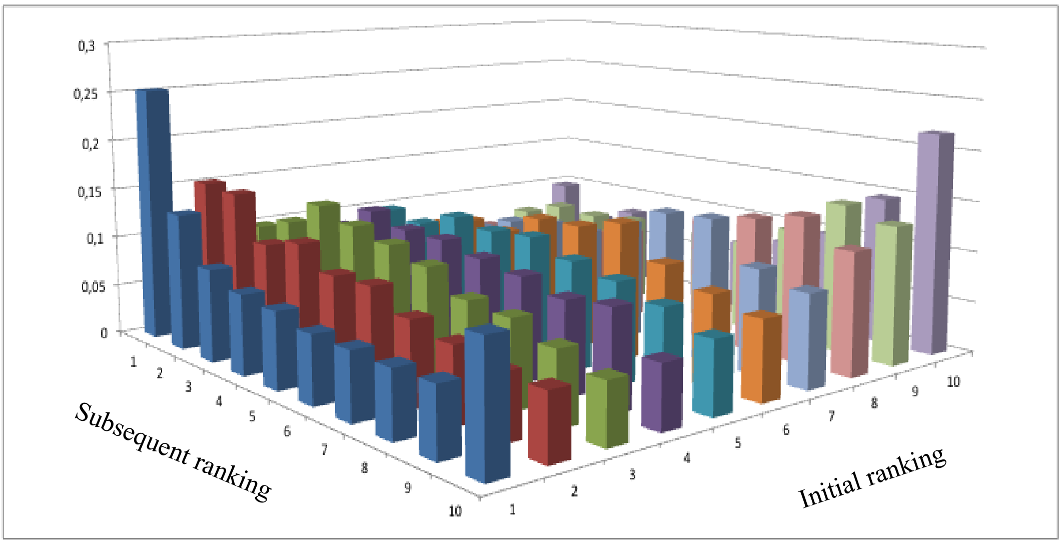


Figure 14: Contingency table of the twelve-month holding strategy



7 Limitations and Further Research

This thesis has discovered some interesting facts that are consistent with much of the findings by Carhart (1997) and Bollen and Busse (2005), but not all results are flawless. The first concern is that our sample size is subject to survivorship and incubation bias which may emphasize and overestimate the past simple returns of mutual funds. Second limitation regards time-period bias, as our dataset picks up two financial crises with one of them considered as the largest one since The Great Depression. This problem could influence our conclusions as the results may be time-period specific or the dataset is not a representative sample. In worst case scenario, outliers within the crisis may increase error variance and reduce the power of statistical tests and altering the odds of making both Type I and Type II errors.

As mentioned earlier, mutual fund performance has been a hot topic and studied by a vast amount in the last decades. However, there are still many elements that have yet to be covered. For instance, academic works lack economic explanation on significant persistence concentrated in underperformance by the loser mutual funds. Most of the previous research focuses on long term persistence and not many on short-term. We believe a further research on either persistence in underperformance or short-term of weekly or daily mutual fund performance could be beneficial with regards to finance literature.

8 Conclusion

We have been applying three methods to analyze the persistence in our sample consisting of US equity mutual funds. The first one involve ranking mutual funds into portfolios based on their previous year simple returns and regressed against three different factor models. The second adds market timing dummy within the factor models. The last methods are graphical illustrations. Consistency in ranking is displayed in a column chart that shows initial ranking and subsequent ranking of the following period with historical probabilities. These three methods are implemented for three different holding strategies: they rebalance every quarter, semi-annual and annual.

The equally weighted portfolio consisting of all funds has performed similar to the benchmark used in terms of excess return, with small differences in standard deviation. This suggests that the mutual fund industry on whole is not able to persistently beat the market and that the benchmark is suitable.

There is a clear trend in all three holding strategies; funds with high past simple returns yield higher excess returns the subsequent period compared to other funds. This implies that in terms of excess returns, some persistence is detected. The risk-adjusted alphas increase as rankings and excess returns increase, with the top portfolios having the highest alpha in all three strategies and gradually diminish in lower ranked portfolios. However, none of risk-adjusted alphas are significant different from zero, except for portfolios 6 and 7 that exhibit significant negative alphas in all three holding strategies, which implies persistence in underperformance. It is hard to draw any solid conclusion why those two in particular, but the results and previous findings suggest that the significances appear randomly within loser performers. In addition, the significant underperformed portfolios (with respect to negative abnormal returns) are the only ones that show insignificant exposure towards one-year momentum effect, when the rest have significant increasing exposure based on its ranking. This indicates that underperformed portfolios are more likely to exclude momentum strategies.

Sharpe ratio follows a similar fashion with the excess returns and risk-adjusted alphas. It increases with portfolio ranking. More frequent rebalancing seems to affect the Sharpe ratio, as the three-month holding strategy clearly outperforms in the top ranked portfolios. However, ranked portfolios with significant negative alpha entail highest Sharpe ratio in the less frequent trading strategies, namely six-month and twelve-month.

As for market timing, the top portfolios all exhibit negative coefficients which is equivalent to no market timing abilities. Carhart 4-factor model shows no significance among the ranked portfolios, not even at the 10% levelm, but CAPM and Fama and French 5-factor model find significance at 5% level on the worst portfolio and its sub-portfolio. It is believed that the reason lies at the exclusion of momentum factor, as signs of marking timing ability appear in the models without factors that capture momentum effects.

For the purpose of investigating persistence in our defined time horizon, the findings show that CAPM performs relatively worse than Carhart 4-factor and Fama and French 5-factor model in terms of explaining the cross-section variation in risk-adjusted returns and in market timing ability. In addition, we find no evidence that the new 5-factor model exhibit more explanatory power than the Carhart 4-factor model in general, due to its exclusion of the momentum factor.

There are quite large variations in consistency in ranking between the holding strategies. For the three month holding strategy there appears to be fairly persistent in top (bottom) performing funds with 60% probability of remaining in the same position. However, the probabilities drop substantially to approximately

25% with the holding periods of six and twelve months. This shows a clear indication of shorter-term persistence in sample returns. The biggest difference between the strategies may be the fact that the possibility of top (bottom) funds wind up as the bottom (top) funds in subsequent period is almost non-existent in the three month holding strategy, whereas the probabilities increase to 10% in the six and twelve month holding strategies. While there is still some persistence left when we move to six and twelve months, most of the rankings appear largely random.

Consistency in ranking cannot be used to reject any market efficiency, as these patterns do not take into account the size of the returns being earned, which makes them unsuitable to draw any clear conclusions towards market efficiency. The risk-adjusted alphas and market timing serve as a better indicator of efficiency. The results from the factor models are more or less consistent as they demonstrated that investors could not have realized positive abnormal returns by replicating any of the three different strategies. The small signs of persistence detected are on the loser side, which does not reject the weak form of Efficient Market Hypothesis. It is therefore reasonable to conclude that the US equity mutual fund market appears to be efficient in the context of this thesis. As a final note, there exist various different approaches to test the market efficiency and persistence as the sorting windows and holding periods can be combined in an almost infinite way by using daily, weekly and monthly data. Hence, there is still much research that can be done regarding persistence in the mutual fund market.

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Appendix

Table 11: Descriptive statistics on ranked portfolios

				Six-month			
Portfolio	Monthly Excess Return	St.Dev.	SR	Max	Min	Kurtosis	Skewness
1A	0,75 %	5,74 %	13,07 %	16,47 %	-30,81 %	4,9853	-1,2811
1	0,70 %	5,06 %	13,84 %	14,98 %	-24,81 %	3,4897	-1,0548
2	0,62 %	4,56 %	13,68 %	13,55 %	-18,89 %	1,7321	-0,6947
3	0,52 %	4,59 %	11,26 %	12,89 %	-18,89 %	1,6922	-0,6673
4	0,46 %	4,57 %	10,06 %	12,47 %	-19,49 %	1,7940	-0,7304
5	0,44 %	4,57 %	9,56 %	12,69 %	-19,53 %	1,7718	-0,6945
6	0,36 %	4,58 %	7,94 %	12,46 %	-19,64 %	1,6334	-0,6797
7	0,33 %	4,61 %	7,21 %	12,40 %	-19,47 %	1,5049	-0,6194
8	0,34 %	4,64 %	7,36 %	12,65 %	-20,14 %	1,8327	-0,6968
9	0,35 %	4,87 %	7,27 %	14,59 %	-20,47 %	1,6913	-0,6160
10	0,23 %	5,49 %	4,23 %	15,66 %	-20,54 %	1,1156	-0,3650
10C	0,08 %	6,35 %	1,26 %	17,52 %	-19,52 %	0,7246	-0,1607
1 - 10	0,47 %	3,62 %	12,94 %	11,56 %	-11,15 %	0,9805	-0,1425
All funds (EW)	0,44 %	4,64 %	9,40 %	12,27 %	-20,19 %	1,8232	-0,7006

All numbers are based on monthly returns in the time period 2001:01 - 2015:12

Table 12: Descriptive statistics on ranked portfolios

				Three-month			
Portfolio	Monthly Excess Return	St.Dev.	SR	Max	Min	Kurtosis	Skewness
1A	0,79 %	5,39 %	14,69 %	13,22 %	-17,76 %	0,9417	-0,7765
1	0,71 %	4,87 %	14,52 %	11,40 %	-19,15 %	1,5807	-0,9062
2	0,60 %	4,55 %	13,12 %	11,36 %	-19,59 %	1,9166	-0,8385
3	0,52 %	4,56 %	11,35 %	12,09 %	-18,94 %	1,6482	-0,7579
4	0,47 %	4,55 %	10,33 %	12,01 %	-19,09 %	1,6833	-0,7295
5	0,43 %	4,53 %	9,39 %	12,39 %	-18,45 %	1,4276	-0,6670
6	0,36 %	4,54 %	8,03 %	12,50 %	-19,14 %	1,5575	-0,6513
7	0,33 %	4,65 %	7,01 %	13,79 %	-20,40 %	1,9449	-0,5890
8	0,34 %	4,70 %	7,21 %	12,95 %	-20,32 %	1,8089	-0,6065
9	0,35 %	4,96 %	7,10 %	13,77 %	-22,41 %	2,1878	-0,6157
10	0,26 %	5,70 %	4,60 %	19,23 %	-24,40 %	2,0008	-0,3443
10C	0,15 %	6,60 %	2,23 %	25,77 %	-24,63 %	1,8846	-0,0383
1 - 10	0,45 %	3,81 %	11,67 %	11,56 %	-12,26 %	0,9543	-0,3147
All funds (EW)	0,44 %	4,64 %	9,40 %	12,27 %	-20,19 %	1,8232	-0,7006

All numbers are based on monthly returns in the time period 2001:01 - 2015:12

Table 13: Linear regression validity test

OLS Annual

	White Test		Breusch-Godfrey 12 lags		Jarque-Bera				
Portfolios	Obs*R^2	P-value	(T-r)*R^2	P-value	T-stat	P-value			
1	23,36	0,0001	18,74	0,0948	25,80	0,0000	Hetero	Non-norm	
2	24,16	0,0001	13,67	0,3499	23,05	0,0000	Hetero	Non-norm	
3	35,69	0,0000	9,85	0,6289	22,69	0,0000	Hetero	Non-norm	
4	31,12	0,0000	19,60	0,0748	14,65	0,0000	Hetero	Non-norm	
5	38,91	0,0000	18,64	0,1000	18,80	0,0000	Hetero	Non-norm	
6	47,21	0,0000	11,06	0,5238	0,54	0,7638	Hetero	Norm	
7	17,58	0,0015	8,48	0,7463	40,26	0,0000	Hetero	Non-norm	
8	9,65	0,0468	17,59	0,1289	70,21	0,0000	Hetero	Non-norm	
9	5,36	0,2525	14,77	0,2542	38,13	0,0000	Homo	Non-norm	
10	4,00	0,4054	15,42	0,2195	36,86	0,0000	Homo	Non-Norm	
1-10	12,43	0,0144	16,40	0,1736	20,76	0,0000	Hetero	Non-norm	
1A	24,08	0,0000	15,51	0,2145	8,66	0,0131	Hetero	Non-norm	
10C	5,63	0,2285	23,27	0,0255	13,80	0,0010	Homo	Non-norm	Auto
1A-10C	10,84	0,0284	9,68	0,6439	7,76	0,0206	Hetero	Non-norm	

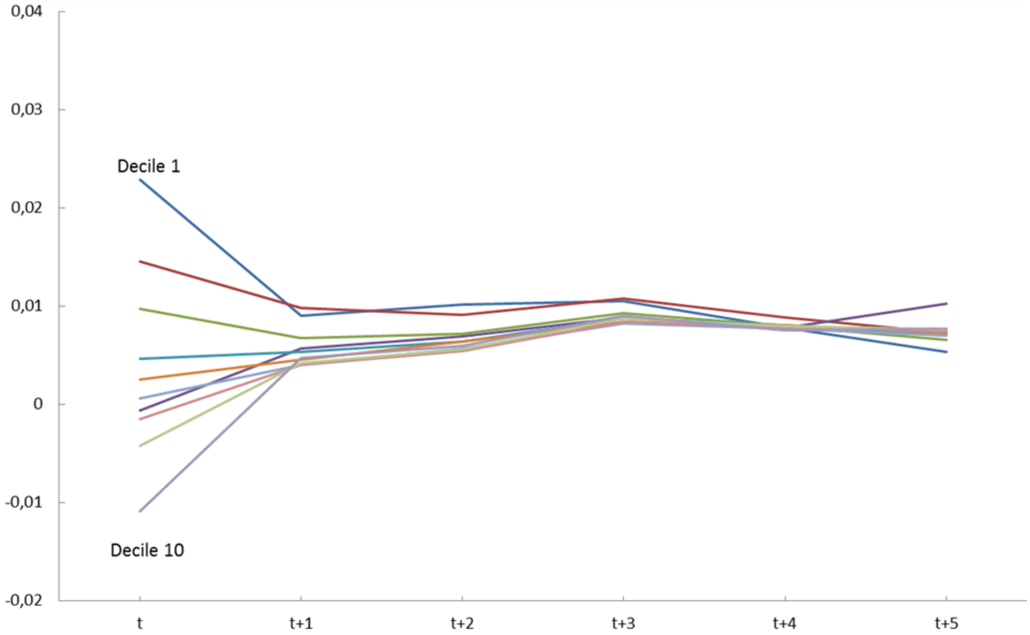
OLS Semi-Annual

	White Test		Breusch-Godfrey 12 lags		Jarque-Bera			
Portfolios	Obs*R^2	P-value	(T-r)*R^2	P-value	T-stat	P-value		
1	21,37	0,0003	15,13	0,2345	18,52	0,0000	Hetero	Non-norm
2	21,53	0,0002	14,55	0,2669	8,94	0,0114	Hetero	Non-norm
3	71,30	0,0000	10,66	0,5587	12,57	0,0018	Hetero	Non-norm
4	35,76	0,0000	12,86	0,3791	11,53	0,0031	Hetero	Non-norm
5	48,26	0,0000	11,95	0,4501	10,90	0,0043	Hetero	Non-norm
6	40,99	0,0000	13,24	0,3515	1,01	0,6040	Hetero	Norm
7	18,02	0,0012	11,34	0,4999	38,99	0,0000	Hetero	Non-norm
8	16,66	0,0022	17,48	0,1325	64,12	0,0000	Hetero	Non-norm
9	8,09	0,0884	10,33	0,5869	53,88	0,0000	Homo	Non-norm
10	6,63	0,1565	11,62	0,4763	57,44	0,0000	Homo	Non-Norm
1-10	23,62	0,0001	8,84	0,7166	9,52	0,0086	Hetero	Non-norm
1A	33,08	0,0000	16,34	0,1763	36,48	0,0000	Hetero	Non-norm
10C	20,20	0,0005	11,00	0,5288	22,95	0,0000	Hetero	Non-norm
1A-10C	34,85	0,0000	6,42	0,8932	24,88	0,0000	Hetero	Non-norm

OLS Quarterly

	White Test		Breusch-Godfrey 12 lags		Jarque-Bera				
Portfolios	Obs*R^2	P-value	(T-r)*R^2	P-value	T-stat	P-value			
1	3,25	0,5170	16,56	0,1669	24,32	0,0000	Homo	Non-norm	
2	18,98	0,0008	17,04	0,1479	15,76	0,0003	Hetero	Non-norm	
3	31,27	0,0000	12,77	0,3859	13,77	0,0010	Hetero	Non-norm	
4	36,55	0,0000	13,14	0,3589	20,78	0,0000	Hetero	Non-norm	
5	45,06	0,0000	8,13	0,7748	5,05	0,0802	Hetero	Norm	
6	32,08	0,0000	12,85	0,3799	0,99	0,6081	Hetero	Norm	
7	63,20	0,0000	16,00	0,1914	11,96	0,0025	Hetero	Non-norm	
8	11,63	0,0203	12,00	0,4460	86,15	0,0000	Hetero	Non-norm	
9	9,06	0,0597	14,20	0,2879	580,14	0,0000	Homo	Non-norm	
10	7,54	0,1099	14,53	0,2684	19,06	0,0000	Homo	Non-Norm	
1-10	8,03	0,0905	7,58	0,8168	8,76	0,0125	Homo	Non-norm	
1A	1,13	0,8890	24,92	0,0152	18,58	0,0000	Homo	Non-norm	Auto
10C	5,22	0,2651	16,15	0,1843	38,28	0,0000	Homo	Non-norm	
1A-10C	5,02	0,2851	8,74	0,7253	5,68	0,0585	Homo	Norm	

Figure 15: Post-formation returns on ranked portfolios with six-month holding period



Each year from 2001:01 to 2015:12, funds are ranked into equal-weight portfolios based on the one-year previous simple return. The lines in the graph represent the excess return on each portfolio in the year prior to the initial year, and in each of the next five years post formation. Decile 1 consists of the funds with the highest formation year returns and funds with the lowest comprise decile 10.

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Table of contents

Introduction

Motivation

The capital market is continuously growing and evolving as time passes, consequentially leading active managers to adapt the innovation with the goal of outperforming the market. We often come across news about fund managers that achieves returns far above corresponding benchmark; for instance, Fidelity Select Biotechnology Portfolio (Money.US.News 2015) 3-year total return is 29.75% (09.30.2015) whereas the fund's benchmark, S&P 1500 Health Care only had a yield of 11.87%. This is only one example, a more thoroughly research, we can find large amount of funds that have generated higher returns for their investors than what the benchmark could have accomplished.

However, can these selected managers consistently provide superior returns in terms of risk associated to their portfolios? Arguably, non-professional investors have "chasing returns" behavior, thus we believe that it is important to distinguish between skill and luck of the managers' performance such that investors with limited financial knowledge are not fooled by the raw historical returns of the portfolio. Hence, it is important to address the risk level entailed in the strategies of the manager in order to justify their abilities. Another important feature may be fees charged by the fund managers, as it may eliminate all potential excess returns.

For several decades, mutual funds have been a very popular saving alternative for households. In terms of value, the funds far exceed trillions of dollars, becoming one of world largest saving options and it is still growing. Clearly, debate of active fund management emerges among academia and investors, leading to perform several studies regarding persistence in mutual fund performance. Even though to already existing studies, the market has indisputably changed today, as one can assume new strategies have been imposed and it is our point of interest to investigate whether the results are different today.

Economic problem

As mentioned earlier, mutual fund performance is a well-known topic and has already been vastly studied. The existing literature provided us insightful information regarding performance, where we recognized a tendency that the more recent studies, the less likely the research is to support consistent excess performance in mutual funds against the comparable market benchmark (see section *literature review* below).

Our main objective is to perform our very own research and check whether the results are the same on the market today vs. market earlier. In other words, we would like to investigate if mutual fund managers can consistently outperform a comparable benchmark. Our main focus will be mutual funds in US with a time horizon in a time period between 2005 and 2015.

We will base our topic with following definition of active management: "Active management is the attempt to improve performance either by identifying mispriced securities or by timing the performance of broad asset classes"(Bodie, Marcus and Kane 2014). Furthermore, we will conduct our research with a null hypothesis that active management will not be able to consistently outperform the comparable benchmark. The models we have decided to use are; Fama-French´s three factor model, Carhart´s four-factor model in addition to two relative new models, Fama-French's five-factor model and Hou, Xen and Zhang q-factor model. The main approach we will use to measure performance will be Jensen's Alpha.

Literature review

The previous studies that we found of most importance related to our research topic are briefly summarized in the next paragraphs, where we include studies both for and against active management.

Based on the efficient market hypothesis (Fama 1970), mutual funds should not be able to outperform the market and make excess returns. In his article, Fama found that the EMH held up well, with very few exceptions. Based on this, mutual fund managers should be unable to make excess returns. However, if and only if the manager possesses superior information, they might get a competitive advantage and perform better than the appropriate benchmark.

Research in favor of passive management

In 1984, Roy Henriksson (1984) applied the basic model of market timing developed by Merton (1981) to 116 open-end mutual funds for the period 1968-80. The empirical results do not support the hypothesis that fund managers are able to follow a strategy that successfully times the return on the market portfolio. Only three funds of the 116 had significantly positive estimates of market timing and only one fund were significant in both sub periods when the sample was split in half.

According to Malkiel (1995) who studied mutual fund performance from 1971 to 1991, concluded that most investors would be better off by purchasing a low expense index fund than buying an active mutual fund. Active management generally fails to provide any abnormal returns and investing in an active fund has a higher tax burden for the investor. Malkiel found that mutual funds tend to underperform the market, even before the management expenses have been accounted for.

In their paper "*Luck versus Skill in the Cross Section of Mutual Fund Returns*" Eugene F. Fama and Kenneth R (2010). French concluded that mutual fund investors in aggregate, yield net returns that underperforms their benchmarks by about the same as the costs in expense ratio. This implies that if there is in fact existence of managers with superior stock picking skills, it is hidden in the aggregate results by the performance of managers with insufficient skills. They also tested 3156 individual funds, and found that only a few funds have enough skill to cover costs when corrected for luck.

Barras and Scaillet (2010) applied a new method to distinguish between skilled and unskilled fund. They found that the amount of skilled managers has diminished rapidly over the past 20 years, while the amount of unskilled managers has substantially increased. Most actively managed funds provide either positive or zero net-of-expense alphas, which make them at least equal to passive funds, and the main reason for actively managed fund's underperformance is due to the long-term survival of a minority of truly underperforming funds.

Research in favor of active management

Article by Gruber (1996) explains why investors buy actively managed open end mutual funds, when in fact mutual funds, on average, offer a negative risk adjusted return and that investor usual gets better outcome by investing in index funds. Gruber argued that future performance is in part predictable from past performance, because the price of a fund does not reflect whether or not it has superior management. A group of well-informed investors seems to recognize this and benefit from it, since those funds outperform the average active and passive funds.

Article proposed by Grossman and Stiglitz (1980) , argued that a state where all information is available with no presence of arbitrage opportunities is not obtainable, so one should not expect that security prices fully incorporates information possessed by informed individuals. They believed there are arbitrage opportunities for those who were able to gather superior information, given that the return of the arbitrage opportunity is higher than the cost of gathering the information. Hence, we should expect some fund managers to possess an informational advantage, at least for some time period.

Carhart (1997) constructed a four-factor model that incorporated Jegadeesh and Titman's momentum factor (1993) to Fama-French's three-factor model (1993). He measured mutual fund performance and found that funds with high past alphas demonstrate relatively higher alphas and expected returns in the subsequent period .This only offers very slight evidence in favor of skilled or informed fund managers as these results are not robust to model misspecification. The top mutual funds are at best able to earn back their investment expenses with higher gross returns. Overall, Carhart's study is consistent with market efficiency, and most funds underperform by approximately the same as their investment expenses.
In an article by Wermers (2000), he used data from 1975 to 1994 and measured the performance of the mutual fund industry. He found that the mutual funds held stock portfolios that outperformed a broad market index by 1.3% per year, whereas 70bp is due to superior stock picking skills. However, on a net-return

level, the funds underperform by 1% per year. The main reason for this is the transaction costs and expenses. Their studies also exclude the tax benefits you would get from passive index funds.

Bollen and Busse (2005) studied persistence in mutual fund performance emphasizing short measurement periods. They ranked funds every quarter by their risk-adjusted return measured over a three-month period. Over this short horizon they found evidence of persistence using the four-factor model for the top decile funds. The results are robust across the momentum factors, which contradicts Carhart’s result, who found no evidence of superior ability after controlling for the momentum anomaly in his paper from 1997.

More recent studies have tried to improve on the existing factor models created by Carhart and Fama and French. Hou, Xue and Zhang (2015) examined close to 80 anomalies and found two major findings. First, one-half of the anomalies earn insignificant average returns, which indicate that many claims in the anomalies literature seem exaggerated. Second, they created an empirical model consisting of the market factor, a size factor, an investment factor, and a profitability factor. They called it the q-factor model, and it outperformed the original Fama-French three factor model and Carhart’s four factor model in capturing significant anomalies that summarize cross section of average returns.

Since the well-known three factor model created by Fama-French back in 1993, it has received significant amount of criticism by numerous researchers, such as, Novy-Marx (2012), Titman, Wei, Xie (2004), etc. They criticized that the model were unable to capture much of the variation in average returns related to significant risk factors, namely investment and profitability. Hence, Fama-French responded this by introducing a five factor (2015) with the inclusion of these two independent variables. They argued that this five-factor model did indeed perform better than the three-factor model, as they found significant patterns in average returns related to size, book-to-market, profitability, and investment. Addition of profitability and investment factors, the value factor of the original FF three-factor became redundant for describing average returns in the sample they examined.

Theory

The importance of Modern Portfolio Theory & Capital Asset Pricing Model

Capital asset pricing model is essentially the building block for our topic, and can be treated as the mother of all models we are about to use. We believe it is important to understand where CAPM originates from and why it is still widely used today for estimating cost of capital, prices and evaluation of mutual fund performance.

CAPM was first introduced by financial economists; Jack Treynor (1961), William F. Sharpe (1964), John Lintner (1965) and Jan Mossin (1966). Each of them had built their work from the foundation of modern portfolio management (MPT) by Harry Markowitz (1952). MPT assumes investors being risk averse with sole purpose of minimizing the variance of portfolio return, given expected return, and maximizing expected return, given variance.
As result, Markowitz constructed the efficient frontier, which is a combination of individual assets that yield highest return given the level of risk. Thus, portfolios on the efficient frontier are considered as mean-variance efficient.

Figure 1

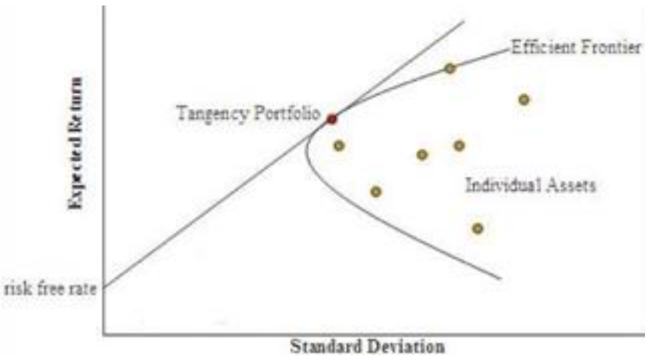

Figure 1 is an illustration of Markowitz model with the function of lending and borrowing at risk free rate. We have expected return on y-axis and standard deviation on x-axis. Assuming that we are able to borrow and lend at risk free rate, we obtain tangency point, which is the market portfolio. Market portfolio is a portfolio that includes every type of assets in financial world where each asset is weighted in proportion to the entire value of the market. This is due to the fact that risk-free investments involve borrowing and lending among investors, as both will cancel each other, respectively. Thus, we achieve market portfolio, where all rational investors should hold their risky assets in the same proportion as their weights in the market portfolio.

The tangency line is known as capital asset line (assuming homogenous expectations), which is defined as:

$$R_p = R_f + \sigma_p \frac{(R_m - R_f)}{\sigma_m} \quad (3.0)$$

This equation implies that the return of a portfolio is equal to the risk free rate plus a risk premium. Note that only efficient portfolios are on the CML (I.e. portfolios that do not possess any diversifiable risks).

CAPM is an extension of MPT. Since Markowitz model is only able to calculate the expected return or price on *portfolios*, CAPM is able to price absolutely any asset. Proving CAPM is outside of our topic, but CAPM entails the same assumption as MPT, including two additional key assumptions, that is the ability to borrow and lend at risk free rate and that all investors have homogenous expectations. In contrast to MPT, the CAPM equation is commonly defined as:

$$E(R_i) = R_f + \beta_{im}[E(R_m) - R_f] \quad (3.1)$$

Where expected return on asset *i* is equal to risk free rate plus market premium times the sensitivity of expected return on asset to the expected return on market return, denoted as beta.

$$\beta_{im} = \frac{Cov(R_i, R_m)}{\sigma^2(R_m)} \quad (3.2)$$

High value of beta indicates higher volatility, contrary to low value of beta implies low volatility, and beta of 1 gives a perfect linear relationship.

Figure 2

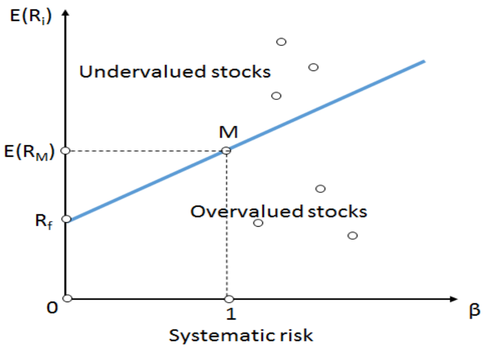

Figure 2 is a graphical representation of the notion embodied in CAPM. The difference between figure 1 and figure 2 is that CAPM provides different measurement. The line in figure 2 is known as security market line (SML), which graphs individual asset risk premiums as a function of beta. Contrary, CML graphs the risk premiums of efficient portfolios as a function of standard deviation. Note that SML is valid for both efficient portfolios and individual assets. CAPM states that investors should be only rewarded for systematic risk, and not unsystematic risk. I.e. all securities that are fairly priced must lie on the SML in market equilibrium, implying stocks that deviates from SML are subject to mispricing.

Security market line provides a benchmark for the evaluation of investment performance. Succession of superior management is dependent on finding and picking stocks that are undervalued. A common method is to use *Jensen's Alpha* (1968) as a tool of performance measurement, which is the difference between the actual and expected returns.

$$\alpha_p = R_p - [R_f + \beta_{im}(R_m - R_f)] \quad (3.3)$$

Positive alpha implies superior performance and negative indicates underperformance. CAPM states that if the stock assets are fairly priced, the expected value of alpha is zero for all securities. Burton Malkiel (1995) found evidence of slightly negative but statistically indistinguishable from zero. I.e. on average, active mutual funds does not outperform the market index on a risk-adjusted basis.

Furthermore, Eugene F. Fama and Kenneth R. French (2004) argued that due to the strictness of the model, CAPM fails to capture entire risk-return relationship. For instance, the market portfolio cannot be observed, which CAPM revolves around, thus at best, we need to use proxy such as S&P 500 and hope that it is sufficiently close enough to the true, unobservable market. However, several researchers such as Keim (1983), Banz (1981), Friend and Blum (1973) and Fama-French (1992) found evidence for funds concentrating on low beta stocks, small stocks or value stocks tends to produce positive abnormal returns relative to the predictions of CAPM, even when fund managers didn't possess superior stock picking skills. The empirical failings are serious enough to invalidate most applications of the CAPM. However, CAPM is nonetheless a fundamental concept of portfolio theory and asset pricing, in which more complicated models originate from.

Efficient market hypothesis

A market is said to be efficient when asset prices reflect all available information, according to this hypothesis as new information about a security becomes available, its price would quickly adjust to the market consensus estimate of its value (Bodie, Marcus and Kane 2014). It is common to distinguish between three different forms of the efficient market hypothesis (EMH): weak, semi strong and strong form. Weak form asserts that prices already reflect all information regarding market trading data such as past prices and trading volume.

Semi strong hypothesis states that all publicly available information regarding the prospects of a firm must be reflected in the stock price. In addition to past prices and trading volume this includes balance sheet composition, quality of management, earning forecasts and so on. If investors have information regarding this, it is expected to be reflected in the stock price.

The strong form is the most extreme hypothesis, and it states that stock prices reflect all information relevant to the firm, including information that only company insiders know about. The one thing all three versions of the EMH have in common is that prices should reflect available information, which is why market prices are not always correct, but if markets are rational, it is expected that they will be correct on average.

This is an important theory to our thesis, because if the efficient market hypothesis holds, it might be more rational to invest in passive index funds compared to actively managed mutual funds as EMH suggests that on average, mutual fund managers do not possess information that is not incorporated in the stock prices. However, there are several known anomalies that contradict the EMH. One anomaly is momentum; good or bad recent performance tends to continue albeit for a short horizon. Another anomaly is investors' overreaction. De Bondt and Thaler (1985) constructed winner and loser portfolios for NYSE stocks (1929-1982) and found that the loser portfolio of 35 stocks outperformed the market by 19,6% while the winner portfolio underperformed by 5%.

Arbitrage pricing theory

Arbitrage opportunity occurs when an investor can make riskless profit without making a net investment. It is an exploitation of price differences of identical or similar financial instruments, on different markets or in different forms. Mispriced securities are a result of market inefficiencies, where arbitrage is considered as a mechanism that restores prices to be in equilibrium in the long run. Arbitrage pricing theory (APT) was first proposed by the economist Stephen Ross (1976). APT is somewhat very similar to CAPM, but differs from the CAPM by being less restrictive on its assumptions. Arguably, CAPM may be regarded as a special case of APT, in the sense that security market line obtained by CAPM represents a single-factor model of the asset price. In contrast, arbitrage pricing theory is commonly associated with multifactor model, defined as:

$$r_i = E(r_i) + \beta_{i1}F_1 + \beta_{i2}F_2 + \beta_{i3}F_3 + \beta_{ik}F_k + e_i \qquad (3.4)$$

Where return on security *i* is equal to previously expected value, $E(r_i)$, plus macro factors (surprises), F, times the sensitivity of security relatively to the systematic factors, β_i, and firm-specific events e_i. Note that the arbitrage-pricing model does not contain any form of specific "theory" in the equation. Intuitively, it only relies on the principle of law of one price where it states as: "If two assets are equivalent in all economically relevant respects, then they should have the same market price" (Bodie, Marcus and Kane 2014). However, we need to define the origination of $E(r_i)$, which requires a theoretical model of equilibrium of security returns. $E(r_i)$ is essential the model from our previous discussion, namely SML from CAPM:

$$E(R_i) = R_f + \beta_{im}[E(R_m) - R_f] \tag{3.5}$$

By substituting the risk premium of the market portfolio, we can rewrite it as

$$E(R_i) = R_f + \beta_i RP_m \tag{3.6}$$

As stated earlier, we can now see that CAPM is just a single-factor model. Furthermore, APT assumes that the unsystematic risk, e_i(3.4), is uncorrelated with assets and any systematic risk factors. Next part follows a set of rules and proofs, which are beyond our thesis objective, but we would like to summarize the main important features; adding concept of well-diversified portfolio and tracking portfolio into equation, it transforms into our desired APT model

$$E(r_i) = r_f + \beta_{i1}\lambda_1 + \beta_{i2}\lambda_2 + \beta_{i3}\lambda_3 + \beta_{ik}\lambda_k \tag{3.7}$$

Where λ_k is the risk premium of pure factor portfolio *i* (pure factor = a portfolio with beta = 1 to the factor and beta = 0 to all other factors). Arbitrage occurs when the expected return of a tracking portfolio differentiates from the expected return on the tracked investment, i.e. equation (3.4) yields different results than equation (3.7).

Why APT matters? First of all, it may be considered as a revolutionary model in the sense that it allows user to customize the model to the security being analyzed. The model does not require like the benchmark portfolio in CAPM to be the true market portfolio, but can be any well-diversified portfolio, which leads to higher flexibility. APT allows multiple sources of risk to explain the variation of an asset's return and mainly uses arbitrage arguments as key driver.

However, the market portfolio is well defined conceptually by CAPM. In APT, the factors are not well specified; hence it may be complicated to determine explanatory risk factors that create equilibrium relationship with an asset's return.

Arguably, it may be close to impossible to detect absolutely every influential factor, and the more betas we estimate, the more statistical noise we include. APT is important to our thesis, as the models we are testing are in fact multifactor models, with different systematic risk factors. As stated earlier, multifactor models expect that there should be no presence of arbitrage opportunity, even with a violation; it will create strong market forces to pressure it back to equilibrium relatively fast. Jensen's alpha is therefore an appropriate indicator of superior performance in APT model; similar to CAPM, if stocks are priced rationally, the expected value of alpha is zero, as the expected return of a manager's portfolio should not plot above the security market line (figure 1) in an efficient market. Thus, returns that deviate from SML, may indicate superior performance/underperformance, or simply due to luck if not consistent.

Methodology

FF Three factor model:

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + e_{it}$$

Where:

R_{it} is the return on security or portfolio *i* for period t

R_{Ft} is the risk-free return

R_{Mt} is the return on the value-weight market portfolio

SMB_t is the return on a diversified portfolio of small minus big stocks

HML_t is the difference between the returns on diversified portfolios of high and low B/M stocks

e_{it} is a zero-mean residual

This model is designed to capture the relationship between average return, size, and relationship to price ratios such as book to market. The model explained two of the well-known patterns that was left unexplained by the CAPM of Sharpe (1964) and Lintner (1965).

FF Five factor model (FF 2014):

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it}$$

RMW_t is the difference between the returns on diversified portfolios of stocks with robust and weak profitability
CMA_t is the difference between the returns on diversified portfolios of stocks of low and high investment firms.

As mentioned earlier, the five factor model were created as a result of empirical evidence presented by Novy-Marx (2012), Titman, Wei, Xie (2004) who showed that the three-factor model failed to capture much of the variation in average returns related to investment and profitability.

Carhart four factor model:

$$r_{it} = \alpha_{iT} + b_{iT} RMRF_t + s_{iT} SMB_t + h_{iT} HML_t + p_{iT} PR1YR_t + e_{it}$$

Where:
r_{it} is the return on a portfolio in excess of the risk-free rate
RMRF is the excess return on a value-weighted aggregate market proxy

SMB, HML and PR1YR are returns on value-weighted, zero-investment, factor-mimicking portfolios for size (small minus big), book-to-market, and one-year momentum in stock returns.

This model is constructed by using FF three-factor model including an additional factor from Jegadeesh and Titman’s (1993) one-year momentum anomaly.

Hou, Xue and Zhang q-factor model:

$$r_t^i - r_t^f = \alpha_q^i + \beta_{MKT}^i MKT_t + \beta_{ME}^i r_{ME,t} + \beta_{\frac{I}{A}}^i r_{\frac{I}{A}}, t + \beta_{ROE}^i r_{ROE,t} + \varepsilon^i$$

Where:

MKT_t is the market excess return

$r_{ME,t}$ is the difference between the return on a portfolio of small minus one with big size stocks

$r_{I/A}$ is the difference between the return on a portfolio of low investment stocks and return on a portfolio of high investment stocks

r_{ROE} is the difference between the return on a portfolio of high profitability (return on equity) stocks and return on one with low return on equity.

This model tries to capture many of the anomalies that the original three-factor model by Fama and French (1993) were unable to capture. The model is in part inspired by investment-based asset pricing.

Performance measure

Jensen's alpha

Jensen (1968) proposed a measure for the performance of a portfolio based on the Capital Asset Pricing Model (CAPM) that aims to determine abnormal returns.

$$\alpha_p = \left(R_p - R_f\right) - \beta_{im}\left(R_m - R_f\right)$$

If the alpha of a portfolio is positive and statistically significant, it would imply that the fund is able to earn abnormal returns. CAPM, FF three-factor and Carhart's four factor model has been heavily used to measure Jensen's alpha, we will in addition to these measure it by using two new models, FF five-factor model and Hou, Xue and Zhang's q-factor model.

Data

Since we are using several models to measure mutual fund performance in US, we need available data on the US market. We believe that the best platforms for gathering sufficient mutual fund data are DataStream and Bloomberg, which both are available at BI, but we do not exclude the possibility of acquiring data from other sources.

For our main analysis our data will consist of the most recent 10-year time period, in which may require to divide the dataset into sub periods in order to check if there are presence of persistence prior and post financial crisis due to potential change in investment strategy. Increasing our time horizon should in theory improve the statistical data set, but it would most likely introduce other statistical problems, such as an increased probability of survivorship bias, and less funds available for sampling. In our analysis we will not include any closed down funds, i.e. only “successful” funds. Including any closed down funds would make it more complicated and probably less accurate to measure performance. We are aware that our analysis may be subject to survivorship bias for this reason.
We will only look at actively managed equity mutual funds US funds that are mainly invested in the US market. We will most likely focus on mutual funds using the benchmark S&P 500 or Russel indices as Cremers et al. (2012) demonstrated that using these commonly used and heavily traded benchmarks provide better performance evaluation. For the risk-free rate we will use the 1-month Treasury bill rate, which is also commonly used when measuring mutual fund performance in the US.

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