Lappeenranta University of Technology

School of Business and Management

Strategic Finance

Ville Valtakari

THE PERFORMANCE OF EUROPEAN SMALL CAP EQUITY FUNDS

Master’s Thesis

Examiners:

Professor Eero Pätäri
Associate Professor Sheraz Ahme

ABSTRACT

Author:	**Valtakari, Ville**
Title:	**The performance of European small cap equity funds**
Faculty:	**LUT, School of Business and Management**
Major:	**Strategic Finance**
Year:	**2015**
Master's Thesis:	**Lappeenranta University of Technology,**
	63 pages, 25 equations, 12 tables.
Examiners:	**Professor Eero Pätäri**
	Associate Professor Sheraz Ahmed
Keywords:	**Mutual fund performance, persistence, active management, small caps**

The thesis examines the risk-adjusted performance of European small cap equity funds between 2008 and 2013. The performance is measured using several measures including Sharpe ratio, Treynor ratio, Modigliani measure, Jensen alpha, 3-factor alpha and 4-factor alpha. The thesis also addresses the issue of persistence in mutual fund performance. Thirdly, the relationship between the activity of fund managers and fund performance is investigated. The managerial activity is measured using tracking error and R-squared obtained from a 4-factor asset pricing model. The issues are investigated using Spearman rank correlation test, cross-sectional regression analysis and ranked portfolio tests. Monthly return data was provided by Morningstar and consists of 88 mutual funds.

Results show that small cap funds earn back a significant amount of their expenses, but on average loose to their benchmark index. The evidence of performance persistence over 12-month time period is weak. Managerial activity is shown to positively contribute to fund performance.

TIIVISTELMÄ

Tekijä:	**Valtakari, Ville**
Tutkielman nimi:	**Pienyhtiöihin sijoittavien eurooppalaisten osakerahastojen suorituskyky**
Tiedekunta:	**LUT, School of Business and Management**
Pääaine:	**Rahoitus**
Vuosi:	**2015**
Pro gradu -tutkielma:	**Lappeenrannan teknillinen yliopisto, 63 sivua, 25 kaavaa, 12 taulukkoa**
Tarkastaja:	**Professori Eero Pätäri**
	Tutkijaopettaja Sheraz Ahmed
Avainsanat:	**Osakerahastot, menestysmittaus, menestyksen pysyvyys, pienyhtiöt, aktiivisesti hoidetut rahastot**

Tässä tutkielmassa arvioidaan europpalaisten pienyhtiöihin (small cap) sijoittavien osakerahastojen menestymistä vuosina 2008-2013. Menestystä mitataan useilla riskikorjatuilla mittareilla. Lisäksi tutkielmassa selvitetään osakerahastojen menestyksen pysyvyyttä vuoden ja kahden vuoden aikaväleillä. Kolmanneksi työssä tutkitaan salkunhoitajien aktiivisuuden vaikutusta osakerahastojen menestykseen. Tutkimuksessa käytetty aineisto koostuu 88 osakerahaston kuukausittaisista tuottoaikasarjoista.

Tulosten perusteella rahastot menestyivät kustannukset huomioon ottaen hieman huonommin kuin vertailuindeksi. Menestyksen pysyvyydestä ei saatu merkittävää näyttöä. Aktiivisimmin hoidetut ja vertailuindeksistään eniten poikkeavat rahastot menestyivät tarkasteluperiodilla paremmin kuin vähemmän aktiivisesti hoidetut kilpakumppaninsa. Nämä rahastot myös tuottivat keskimäärin paremmin kuin vertailuindeksi.

ACKNOWLEDGEMENTS

First of all, I am indebted to many amazing student colleagues and friends for all the fun and awesome experiences we shared together.

I also take this opportunity to express gratitude to the personnel of LUT School of Business and Management for sharing their expertise and providing a stimulating studying environment. I also want to thank my supervisor Professor Eero Pätäri for the sound advice, comments and counseling especially in the final stages of my thesis.

Lastly, and most importantly, I wish to thank my whole family for the unconditional and endless support and encouragement through my studies and whole life.

Helsinki 15.5.2015

Ville Valtakari

Table of contents

1 INTRODUCTION

1.1 Background

Investors in most parts of the world invest through mutual funds that pool in money from investors and invest on their behalf providing professional money management and diversification opportunities. The global asset management industry has grown to 45 trillion euros in which Europe accounts for 31%. Europe has retained a steady share of approximately one-third of the industry over the past number of years. (EFAMA 2013). One of the mysteries of financial economy is why the financial intermediaries appear to be so highly rewarded despite the uncertainty about whether they add value through their activities.

Risk and performance measurement is an active area for academic research and continues to be vital for investors who need to make informed decisions and for mutual fund managers whose compensation is tied to performance. There are a number of performance measures with a common feature that they measure funds' return relative to risk. For investors the results from various studies across decades have been disheartening. The consensus amongst academics has been that on average a fund manager is not able to outperform the market consistently after expenses have been taken into account (i.e. Jensen, 1968; Malkiel, 1995). For example, Wermers (2000) and Grinblatt & Titman (1989) show that the managers are able to add value but not to the extent that the fees are covered. French (2008) states that both academic and non-academic research reveals that that mutual funds on average fail to beat their benchmark based on net returns earned by the investors. In addition, investors could earn higher net returns by switching to a passive strategy. Despite the increased popularity of passive investing, investors are still paying significant sums of money for a service that has not yet been academically demonstrated to add value. This seems like an economic puzzle.

Most evidence of the academic studies on mutual fund performance has been collected with data that is based on funds investing in large company stocks. Research of funds investing in smaller companies has been constricted, and the aim of the study is to find out whether the results can be carried over to mutual funds investing only in smaller companies. In the enormous global asset management industry small cap funds are particularly interesting. For example, when looking at fund return figures in Morningstar, one will see that small and mid-cap funds have performed better in the long run than large cap funds. Secondly, when investigating the risk-adjusted performance of European mutual funds, Otten and Bams (2002) found that small cap funds were able to add value as indicated by their positive after-cost alphas. So why is this then? Generally speaking, it has been argued that small caps have the ability to produce greater returns through more agile and dynamic businesses that tend to be more growth oriented than larger conglomerates. The fact that smaller companies are often targets for acquisitions and that larger companies are sometimes willing to pay a premium to acquire them makes them more attractive. The smaller visibility within the investment community can also lead to divergences of the stock prices to companies' fundamentals. Thus, temporary undervaluation, thin markets and lack of analyst coverage have been matters of which small cap investors can take advantage. However, some financial economists attribute most of the anomalies to either misspesification of the asset-pricing model or market frictions. For example, the small firm effect is commonly perceived as a premium necessary to compensate investors in small stocks, which tend to be illiquid. Fama (1998) also notes that the anomalies could be viewed as random occurrences that often can be severed using different time periods or methodologies.

Is it still possible that some managers are able to outperform the market net of costs despite the poor results of the average manager? Moreover, if some managers are good at picking stocks, then it is reasonable to believe that such talents persist over time. The literature of performance persistence tries to answer these presumptions. Historical performance is also considered a top criteria of investors when making their decision (Puttonen & Repo 2006). Additionally, one can see ads promoting the stellar performance of "hot" mutual funds in newspapers and magazines. This is understandable as the feature is visible and understandable but is it justified? According to the efficient market hypothesis it should not be possible to predict future performance of any security based on past performance. There are numerous papers devoted to the topic but no common conclusion has been drawn whether performance persists or not. However, the authors seem to agree that if persistence exist, it only does so over short time horizons (i.e. Hendricks et al. 1993; Grinblatt & Titman, 1993; Bollen & Busse 2005; Huij & Verbeek 2007). Theoretical starting point for this topic in the thesis is that the properties of smaller company stocks could leave a larger leeway for skilled managers to stand out. Supporting this presumption Huij and Verbeek (2007) report that within a subgroup of different fund types, persistence is concentrated in relatively young, small cap/growth funds.

In almost all economic endeavors, the quality of management is generally a key component of a successful operation. The proponents of active management, who do not follow the efficient market hypothesis, believe that managing a mutual fund is no exception to that rule. They believe in superior investment skills and thus argue in favor of active portfolios in attempt to systematically generate higher returns than the market. This requires active alteration of portfolio weights over time followed by successful forecasting abilities. A logical consequence of this would be that skilled managers would take larger "bets" away from the market portfolio than less skilled ones to take advantage of his or her superior information. Some fund managers have also been accused of playing it safe by replicating the benchmark index to which his or her performance is usually compared to. This so-called "closet indexing" is often despised by investors since it hardly justifies the fee the funds charge from active management. Instead, investors could switch to a low-cost index fund. In the literature, the level of active management has proven to strengthen the chances of a fund to beat its benchmark (i.e. Chen et al., 2000; Cremers & Petäjistö, 2009), This makes it an interesting starting point to lastly study the effect of managerial activity on the performance of small cap equity funds along the performance and performance persistence.

1.2 Objectives, limitations and methodologies

The thesis contributes to the extensive academic literature of mutual fund performance by concentrating on actively managed European small cap equity funds, a narrow segment not as comprehensively covered. The first objective of the study is to evaluate the risk-adjusted performance of the funds compared to a proper benchmark. Since different risk-adjustment procedures can yield different implications for performance, the performance is measured using several common risk-adjusted measures of portfolio performance. These include Sharpe ratio, Treynor ratio, Modigliani measure, Jensen alpha and the Fama-French 3-factor alpha and Carhart's 4-factor alpha.

Since investors are likely to make investment decisions based on past performance of a fund, the thesis secondly explores whether fund managers possess "hot hands", i.e. are the funds that performed well (poorly) in the past more likely to do so in the next period. To study performance persistence, three different methods are employed. These are Spearman's rank correlation test, ranked portfolio tests and cross sectional regression analysis. The performance persistence is studied over 12-month and 24-month time periods. Spearman rank correlation test is applied to test whether fund rankings in the selection period correlate with the ones in subsequent holding period. For more insight, the funds are also sorted into top and bottom performers on the first period in order to study whether the performance difference between these two portfolios continues in the following period. In the last stage, short-term persistence, existence of which the academics seem to agree is studied using cross-sectional regressions to detect whether the past alphas explain the returns of the next period.

Third objective of the thesis is to identify the effect of managerial activity on the performance measures. The amount of work done by the mutual fund manager is measured using funds tracking error and the R-squared from a linear regression model. The correlation between managerial activity and performance measures is then tested with Spearman rank correlation test. Further, high and low managerial activity portfolios are formed to compare the performance differences.

1.3. Structure of the study

The rest of the thesis is organized into six sections as follows: section 2 introduces the theoretical backgrounds of essential financial and investment theories followed by descriptions of the performance measures. Section 3 starts with a brief history of the mutual fund industry and presents the previous literature of mutual fund performance, especially of topics related to this study. Section 4 for introduces the data and describes the methodology more closely. In section 5 the empirical results are exhibited and briefly discussed. Finally, section 6 summarizes the results. In addition, conclusions are drawn and few suggestions for future research are presented.

2 THEORETICAL BACKGROUND

2.1 Efficiency of the stock markets

Despite the strong growth of passive products in recent years, a dominant share of professionally managed assets follow an active investment strategy.[1] Portfolio managers pursue an above market return arguing being better informed than the average investor. This contradicts one of the cornerstones of modern financial theory, the efficient market hypothesis, EMH, developed by Professor Eugene Fama at the University of Chicago Booth School of Business (Fama, 1970). The theory has been highly controversial and often disputed. The efficient market hypothesis asserts that financial markets are “informationally efficient”. The prices of securities reflect all available information that is available about the intrinsic value of the asset. In consequence of this, one should not consistently be able to achieve returns in excess of average market returns on a risk adjusted basis, given the information available at the time the investment is made.

The random walk theory of stock prices, often brought forth with the EMH, suggests that past movements in stock prices, trend of a stock price or market cannot be used to predict a stock’s future price. The theory was popularized by Malkiel (1973) in his famous and influential finance book A Random Walk down the Wall Street. According to the theory, stock prices should follow “random walk” with the presumption that investors make rational decisions without biases and that the value of the stock is at all times based on future expectations. Under these conditions all existing information affects the price and is only changed with new information. By definition, new information only appears randomly making the asset price move randomly.

Fama (1970) presents three major levels of efficiency, each of which address different types of information. The weak form of the EMH claims that prices of traded assets reflect all past publicly traded information, thus excluding the possibility to make superior profits by studying the past returns. The second, semi-strong form of the EMH additionally claims that prices reflect past information and all publicly

[1] The percentage of index equity mutual funds’ share of funds’ total assets has risen from 9.5% to 18.4% between 2000 and 2013. (2014 Investment Company Fact Book, 2014).

available information. When this criteria is met in the market, the prices instantly change to reflect new public information and corporate announcements. Finally, the third, strong form efficiency additionally claims that prices instantly reflect even hidden or “insider” information about the underlying asset. The performance mutual funds make an interesting test for the semi-strong form efficiency since the fund managers can be considered as financial specialists and might have deeper insight and sometimes easier access to information.

If stock prices have an unpredictable path and markets are efficient in the sense that prices reflect all available information, this should result in a failure in any investment strategy attempting to beat the market. This of course does not support active portfolio management. Due to the management costs, active management should loose against passive one and excess returns should occur only through luck. Although, the EMH applies to all types of financial securities, discussions of the theory usually focus namely on shares of common stock. Academics have pointed out a vast amount of evidence supporting the theory. Believers argue it is pointless to search for undervalued stocks or predict trends through either fundamental or technical analysis. Grossman (1976) and Grossman and Stiglitz (1980) point a critical view of the theory and argue that informationally efficient markets are an impossibility if there are costs of gathering and processing information. The abnormal returns are necessary to compensate investors for the costs of information-gathering and information-processing. Furthermore, if the markets were efficient and the return for gathering information was zero, the markets would eventually collapse because there would be little reason to trade. The degree of market inefficiency will determine the effort to which investors are willing to expend to gather and trade information. In equilibrium, the superior information is not, however, translated into superior net returns because the informed investors are compensated only for the amount of resources spent. Consequently, active and passive investing should yield same net returns.

The efficient market hypothesis was considered to be a remarkably good description of reality up until the late of 1980s when some financial economists and statisticians began to believe that the prices are at least somewhat predictable. Market irrationalities in stock prices involved in the 1987 stock market crash and the Internet

Bubble of the late 1990s provided evidence that stock prices can seriously deviate from their fair values. Some critics point out that investors, such as Warren Buffet have consistently beaten the market over long periods of time. But apart from single stories, other well-known return distortions such as the size effect, the value effect, the momentum effect, the weekend effect, the January effect and the dividend effect have been recorded contradicting efficient market hypothesis (Schwert, 2003). These market anomalies have been considered to represent either profit opportunities or inadequacy of the asset pricing model. Malkiel (2003) interprets specific anomalies as proxies for unknown risk factors rather than inefficiencies. Fama (1998) notes that anomalies are often caused by random occurrences such as market underreaction or overreaction, and they can often be distinguished using different time periods or methodologies.

In the conditions of weak form efficiency, prior stock returns should have no relation to future stock returns. However, Jegadeesh and Titman (1993) documented the momentum effect. They showed that strategies of buying past well performing stocks and selling stocks that have performed poorly in the past generates positive returns over 3-12 month period. They find that the profitability of the strategies is not due to their systematic risk or to delayed stock price reactions to common factors. Fama and French (1993) emphasize the fact that high book-to-market firms and firms with lowest market capitalizations have performed substantially better than those with low book-to-market and highest capitalizations. Considering this study, the abnormally high returns on small firms is particularly interesting. The general discussion is that this could mean several things. First, investors could have demanded higher expected return from small firms to compensate them for some other extra risk factor that is not captured by the asset pricing model. For example liquidity risk is often associated with small firm stocks. Keim (2008) states that even though statistically significant anomalies would exist, transaction costs could prevent market participants to take full advantage of them. Second, it could be a coincidence that stems from the many efforts of researchers who try to find interesting patterns in the data (Brealey et al. 2014). Third, it should be pointed out that as the above mentioned anomalies were first identified in academic papers, investors began to implement strategies to take advantage of them causing the markets to become more efficient. Schwert (2003) shows evidence that size, value, weekend and dividend effects weakened after they were first highlighted in the literature. Malkiel (2003) also states that whatever patterns or irrationalities have been discovered, they are unlikely to persist. He finalizes his paper stating, “If any $100 bills are lying around in stock exchanges of the world, they will not be there for long.”

2.2 Linkage between risk and return

The simplest and widely used performance measure to rank mutual funds are annual returns and they are also applied in this study. Annual returns easily understandable and show the actual returns received after the expenses. However, despite the pros, annual returns do not take into account the risk level of funds. The fundamental concepts of modern portfolio theory by Markowitz (1952) suggest that investors choose from all possible investments based on expected portfolio return and portfolio risk. At a certain level of risk a rational investor will choose the investment that provides highest return or the least risky investment at a certain level of return. The idea of risk is the level of uncertainty for the expected returns to actualize. Sharpe’s (1966) pioneering study about the relationship of risk and return states the expected returns of a portfolio are associated by the variability of returns expressed as the standard deviation of return. Under certain assumptions[2] all efficient portfolios should fall along a straight line known as the Capital Market Line (CML). It results from the combination of the market portfolio and the risk free asset. CML illustrates the rate of return for efficient portfolios depending on risk free rate and the level of risk measured by standard deviation:

$$E_r = r_f + \sigma \frac{E(\, r_m) - r_f}{\sigma_m} \tag{1}$$

The CML describes the expected return of only efficient portfolios. The slope of the CML, $[E(\, r_m) - r_f \,/\sigma_m]$, is the market price of risk because it indicates the market

[2] The investors are assumed to be able to invest at common risk-free rate and borrow money at the same rate. At any point the investors share the same predictions of future concerning the performance of securities and portfolios.

risk premium for each unit of deviation. To characterize how well the return of an asset or investment compensates the investor for the risk taken, Sharpe derived a measure from the CML. The Sharpe ratio measures the risk premium or (excess return) per unit of deviation in an investment portfolio. The Sharpe Ratio is calculated by dividing the excess returns of a portfolio by the standard deviation of the portfolio returns:

$$Sharpe\ ratio = \frac{r_i - r_f}{\sigma_i} \tag{2}$$

where r_i is the return for portfolio i, r_f is the risk-free rate and σ_i denotes the standard deviation of portfolio i.

In fact, the slope of the CML is the Sharpe Ratio of the market portfolio. When comparing investments the one with higher Sharpe ratio provides better return for the same level of risk (or equivalently same return for lower risk). By definition, the Sharpe Ratio is a reward-to-variability measure and it is one of the most common measures of risk-adjusted performance. Ratio-based performance measures are frequently published in media and fund brochures due to their simplicity, practicality and lower data requirements.

Another common ratio-based performance measure is the Treynor ratio, also known as the reward-to-volatility ratio. Like the Sharpe's ratio, the Treynor ratio gives average excess return per unit of risk incurred but instead of total risk, it uses systematic risk expressed as the beta coefficient β_i of a portofolio. (Bodie et al. 2008, 591; Treynor, 1965). Treynor ratio is given as follows:

$$Treynor\ ratio = \frac{r_i - r_f}{\beta_i} \tag{3}$$

Beta, β_i is a measure of volatility and denotes the sensitivity of the assets return to the systematic risk. A beta greater than 1.0 (aggressive stocks) indicates that the security's price will move more volatile than the market. The market by definition, has beta of 1.0. Securities with beta less than 1.0 (defensive stocks) are less sensitive to market swings. Beta can be calculated as the covariance of single assets' return with the market return divided by the variance of market return:

$$\beta_i = \frac{Cov(r_i, r_m)}{Var\ (\ r_m)} \tag{4}$$

Practically, beta is the regression coefficient of the security return on the market return.

The ratio-based performance measures can be used to rank mutual funds based on performance but their numerical values are not easy to interpret. Comparing Sharpe ratios of a fund and a benchmark, say 0.67 and 0.73 show that the latter performs better but not exactly how much since the Sharpe ratio is an absolute measure of reward-to-variability. A variant of Sharpe ratio was introduced by Nobel laureate Franco Modigliani and his granddaughter Leah Modigliani in 1997. They believed that ordinary investors would find it easier to understand results expressed in percentage units. The measure is most commonly known as the Modigliani measure, Modigliani risk-adjusted performance measure (RAP) or the M2 measure (for Modigliani squared). (Bodie et al. 2008, 591-592).

Risk-adjustment for the Modigliani measure is done by leveraging and unleveraging. Given a portfolio with any level of expected return and dispersion of returns, it is possible to obtain any desired level of risk by leveraging. The leveraging is done by borrowing and unleveraging is done by lending at risk free rate. If a share of d% of a portfolio is sold and invested in a risk free asset, the level of dispersion in returns of the portfolio reduces by d%. That is because d% of the portfolio is changed riskless and made constant. The excess return over the risk free rate also reduces by d%. (Modigliani & Modigliani, 1997, 47.) To compute the measure, a managed portfolio is assumed to have a long or a short position in the risk free rate of return in the sense that it matches the risk level of a relevant benchmark. For example, if a managed portfolio has a standard deviation of 1.5 times the standard deviation of the benchmark, the adjusted portfolio would have two-thirds invested in the managed portfolio and one-third in the risk-free asset. The benchmark and the portfolio would then have the same standard deviation, and the performance can simply be done by comparing returns. (Bodie et al. 2008, 592.) The level of leverage required to match the standard deviations can be inferred as d_i from the equation:

$$\sigma_m = (1 + d_i)\sigma_i \tag{5}$$

which implies:

$$d_i = \frac{\sigma_m}{\sigma_i} - 1 \tag{7}$$

Taking into account the interest on d_i we find that Modigliani measure is equivalent to:

$$M2_i = (1 + d_i)r_i - d_i r_f \tag{8}$$

By substituting d_i RAP can be rewritten as:

$$M2_i = \frac{\sigma_m}{\sigma_i} r_i - (\frac{\sigma_m}{\sigma_i} - 1)r_f \tag{9}$$

The Modigliani measure can also be rewritten in a way that it clearly shows its connection to the Sharpe ratio, S_i:

$$M2_i = S_i\sigma_m + r_f = \frac{r_i - r_f}{\sigma_i}\sigma_m + r_f \tag{10}$$

2.3 Return according to the Capital Asset Pricing Model

Where the previously presented measures are commonly used in practical applications when comparing investments, they play only a minor role in more advanced academic work on the performance of mutual funds. The most common approach for risk-based performance evaluation lies rather in asset pricing models. In general, risk-based fund performance evaluation is based on the return gap between a fund and a benchmark portfolio that has the same level of risk. In order to calculate the performance measure, systematic risk of a fund and the expected market return at this risk level need to be determined and subtracted from the realized return of a fund. Commonly, risk-based measures are referred to as alpha because they can be obtained as the intercept term in a regression.

Building on the modern portfolio theory of Markowitz, Sharpe (1964), Lintner (1965) and Mossin (1966) individually laid down basic ideas of the equilibrium model that determines the relationship between risk and expected return of any risky asset. The Capital Asset Pricing Model (CAPM) offers the theoretically appropriate rate of return of an asset in respect to its systematic risk. Systematic risk (or non-diversifiable, or market risk) cannot be avoided through diversification since it arises from fluctuations in economic activity. The other part of risk, unsystematic risk (or diversifiable risk) is assumed to be non-existent since CAPM assumes that the underlying asset is to be added to a well-diversified portfolio. Thus, only the security's sensitiveness to variability of the market portfolio is meaningful when assessing its risk. Prices of securities will adjust until there is a linear relationship between the magnitude of responsiveness to swings in the market and expected return. (Sharpe 1964, 440-442). The equation of CAPM is called the Security Market Line (SML). The previously mentioned Capital Market Line graphs risk premiums for efficient portfolios as a function of standard deviation. In contrast, the SML graphs individual asset risk premiums (which are held as parts of a well-diversified portfolio) as a function of beta. Thus, the SML describes the expected returns on all assets and portfolios, whether efficient or not (Bodie et al. 2008). The general equation of CAPM is the following:

$$E(r_i) = r_f + \beta_i\left[E(r_m) - r_f\right] \tag{11}$$

where $E(r_i)$ is the expected return of an asset, r_f is the risk free rate and $E(r_m)$ is the expected market return, β_i is a measure of volatility and denotes the assets sensitivity to systematic risk.

When used in portfolio management, the SML represents the investment's opportunity cost (investing in a combination of the market portfolio and the risk-free asset). All the correctly priced securities are plotted on the SML. The assets above the line are undervalued because for a given amount of risk (beta), they yield a higher return. The assets below the line are overvalued because for a given amount of risk, they yield a lower return. Moreover, the slope of the SML is, in fact, the Treynor ratio. The logical implication of CAPM is that a passive investing strategy always ends up on SML, being thus efficient. This is inconsistent with the real world: if a passive strategy is also costless, why would any investor use resources in security analysis? In fact, an active investor who chooses any other portfolio, will end up less efficient than the passive investor. This result is sometimes called a mutual fund theorem. However, if no one does security analysis, there would be consequences for the efficiency of the market portfolio. (Bodie et al. 2008). The viability of the mutual fund theorem has been questioned because several important assumptions must be in place for the theorem to be proved. The CAPM, altogether, simplifies certain real world complexities and has some required assumptions. Viswanath and Krishnamurti (2009, 69) list these assumptions as follows:

- Investors make choices on the basis of risk (i.e. variance) and return, meaning that they use Markowitz's portfolio selection model.
- Asset returns are normally distributed.
- Investors have homogeneous expectations of risk and return.
- Investors have identically long holding periods.
- Information is freely available to investors and they analyze the information in the same way.
- There is a risk-free asset and investors can borrow and lend at risk-free rate.
- There are no taxes or transaction costs or restrictions on short selling.
- The true market portfolio defined by the theory behind the CAPM is unobservable. One selects and uses market portfolio proxy.

The reaction to the assumptions might be that they seem unrealistic and could cause failed results. And the model, however being widely used, has faced criticism. Most problems in the evaluation methodology arise when determining the appropriate market portfolio. The applicable market portfolio can only be substituted by market indexes which only contain traded securities. Roll (1977) argues that it is impossible to observe the real market portfolio since it would consist of every single possible asset including bonds, preferred stocks, real estate, precious metals, stamp collections and basically anything worth something.

2.3 Multifactor models: size, value and momentum effect

The discussions contradicting the sufficiency of CAPM proceeded when factors like size, various ratios, and price momentum provided cases of diversion from the models premise. This led to the development of multifactor models. Other variables with no presence in CAPM seemed to have a more significant predicting ability than the beta. Banz (1981) first noticed the size effect. Average return of small firm stocks was substantially higher than the average of larger firms after adjusting for the risk using CAPM. Jegadeesh & Titman (1993) documented the momentum effect that stock prices are likely to keep moving in the same direction as in the most recent history. Fama and French also (1993) started identifying factors consistent with Banz's finding and rational pricing stories that would provide explanatory power. They started with the observation that several studies reported systematic cross-sectional patterns in average stock returns depending companies' market capitalization, earnings/price, cash flow/price book-to-market equity, past sales growth, long term past return and short term past return. They argue that these patterns are not explained by traditional CAPM and thus additional risk factors should be included in the model. Additionally to size effect, they observed the value effect that stocks with high book-to-market ratio (value stocks contrasted with growth stocks) also tended to perform better in the market. As a result they suggest that the effects are economically so important that it questions the validity of CAPM. They come up with a three factor model where firm size and book-to-market-value are additional risk factors needed to explain asset returns. By including these factors, the model adjusts for their outperformance tendency. The generalized equation of the model is the following (Fama & French 1996, 56):

$$E(r_i) - r_f = \beta_i\left[E(r_m) - r_f\right] + s_i\, E(SMB) + h_i\, E(HML) \qquad (12)$$

where, $E(r_i)$ is the portfolio's expected rate of return $(r_m) - r_f$ is the excess return of market portfolio. SMB is the difference between small stock and large stock portfolio returns, HML is the difference between high book-to-market and low book-to market portfolio returns.

Carhart (1997) extends the model even further by adding a momentum factor that captures the one-year momentum effect reported by Jegadeesh and Titman (1993). Momentum factor (MOM as in monthly momentum) was introduced to capture the tendency for the stock price to continue rising if it is going up and to continue declining if it is going down. The equation for Carhart's 4-factor model is given as follows:

$$E(r_i) - r_f = \beta_i\left[E(r_m) - r_f\right] + s_i\, E(SMB) + h_i\, E(HML) + m_i\, E(MOM) \qquad (13)$$

The multifactor beta is similar to the traditional beta. It is a measure of risk relative to the market. However, not identical, since the two or three additional factors affect the results. The SMB stands for "Small Minus Big" in terms of market capitalization and represents the premium that companies with smaller market capitalization usually earn over the firms with larger capitalization. The HML stands for "High Minus Low" in terms of book-to-market ratio and represents the premium that investors expect from companies with high book-to-market ratio over their counterparts with low book-to-market ratio. Respectively, the momentum factor is sometimes referred to as WML that stands for "Winners Minus Losers".

In practice the monthly SMB factor is constructed as the difference between average returns of the smallest 30% stocks and largest 30% stocks. The monthly HML factor is constructed as the difference between average returns between highest and lowest 50% stocks in terms of market-to-book ratio. The MOM factor is constructed by subtracting the equal weighted average of the 30% highest performing firms from the equal weighed average of the 30% lowest performing firms, lagged one month. Between 1926 and 2002 in the US, the average annual size premium has been approximately 3.3% and the average annual value premium approximately 5.1% stating that small cap stocks and value stocks have outperformed large cap stocks and growth stocks when considering cumulative returns (Viswanath & Krishnamurti, 2009, 96-97).

2.4 Alpha-based performance measures

The foundation of academically most recognized risk-adjusted performance measures is the Jensen's alpha introduced by Jensen (1968). It measures whether a portfolio yields a proper return for its level of risk. In other words, it is a measure of abnormal rate of return on a portfolio or a security in excess of what would be predicted by the equilibrium model such as CAPM or the multifactor models. Thus, the alpha is sometimes considered as a measure of managerial stock selection skills. However, it should be noted that the CAPM is derived based the assumption that investors only care about mean and standard deviation of returns. It would also be reasonable to assume that they also care about higher moments such as skewness and kurtosis. In addition, investors dislike downside risk. Downside risk is defined as stocks being more sensitive to market movements when the market goes down as compared to market movements when the market goes up. For example Pätäri (2000) emphasized the importance of measures for downside risk in fund evaluation.

The CAPM equation in its traditional form lacks the opportunity to explain excess returns and thus the equation is slightly restated. When the basic presentation of CAPM is applied statistically, it should be allowed for an error term ε_i which represents arbitrary deviations from forecasted returns:

$$r_i - r_f = \beta_i(r_m - r_f) + \varepsilon_i \tag{14}$$

However, the model still offers no opportunity for performance deviations from its risk level since CAPM assumes normal distribution of returns and thus the expected value of the error ε_i term is zero. As a result an additional constant, alpha is introduced to the model:

$$r_i - r_f = \alpha_j + \beta_i(r_m - r_f) + \varepsilon_i \tag{15}$$

A positive alpha means that fund's return is higher than the hypothetical return of the benchmark portfolio with the same level of risk. This, of course, indicates security selection skills of the portfolio manager. A random buy and hold strategy should produce an alpha of zero. The formula can be further organized in the form where alpha α_j is equal to the portfolios excess return over CAPM:

$$\alpha_j = r_i - [r_f + \beta_i(r_m - r_f) + \varepsilon_i] \tag{16}$$

Respectively, in the multifactor models the intercept α_i is similarly added to the equation:

$$r_i - r_f = \alpha_i + \ \beta_i\left(r_m - r_f\right) + s_i\, SMB + h_i\, HML + \ m_i\, MOM + \varepsilon_i \tag{17}$$

In this case the alpha α_i represents the value that the portfolio manager captures given the exposure to the $(r_m - r_f)$, SMB, HML and MOM factors. The factors can be interpreted as passive benchmark returns that capture the patterns during the sample period, whatever the source of active returns. When the returns associated with the above factors are separated, it allows a better outlook on the effects of active management. If the manager captures the exposures to these factors perfectly, the alpha would be zero. An alpha greater than zero suggests that the manager is adding value beyond what would be justified by market risk and generated through following the known strategies of size, value and momentum investing. (Fama & French, 2010; Carhart, 1997).

2.5 Active portfolio management

Now that the measures of successful portfolio management are presented, the rationale for active management can be considered. An equity fund manager can attempt to outperform the market only by taking positions and that are different from the benchmark index. A positive correlation between active changes in portfolio weights and subsequent asset returns is an appropriate measure of successful active management. This is illustrated by Lo (2008) who presents the expected return of a portfolio $E(r_{it})$ broken down into active and passive components:

$$E(r_{it}) = \sum_{j=1}^{m} Cov\left(w_{ijt,} r_{jt}\right) + \sum_{j=1}^{m} E\left(w_{ijt}\right) E(r_{jt}) \tag{18}$$

where *m* is the amount of individual securities in the portfolio, r_{jt} is the return of asset *j* in time *t* and $w_{ijt,}$ is the corresponding weight in portfolio *i.*

The first term on the right-hand side is the active component. The motivation of the covariance term in the equation refers to the conscious decisions of the portfolio manager to buy, sell or avoid a security. The impact of the decisions on the total expected return of the portfolio is captured by the covariance. The portfolio weights of the active component vary over time with the aim to achieve an improved risk-return trade-off. For example, when the manager has positive weights when security returns are positive and negative weights when security returns are negative, this implies positive covariance between portfolio weights and returns and this will have a positive impact on the portfolios expected return. The second term (passive component) in the equation is another source of potential positive expected return. It refers to the expected return of the portfolio when the portfolio weights are kept fixed. The manager maybe holding passive long positions in securities with positive expected return and passive short positions in securities with negative expected returns. For example, a buy and hold strategy of stocks should contribute positively to the portfolio return because of equity risk premium. (Lo, 2008).

The active component in the equation can be broken down further since the holdings differ from benchmark index in two general ways: in stock selection and factor timing. Among others, Fama (1972) and Daniel et al. (1997) define stock selection as picking particular stocks that manager expects to make a good investment and therefore should be added to the portfolio. Factor timing is based on outlook for an aggregate market rather than for a particular asset. Factor timing results from technical or fundamental analysis and is defined as time-varying predictions on market risk factors such as entire industries, sectors of the economy, or more generally any part of the market risk.

Market efficiency prevails when many investors are willing to depart from a passive strategy and actively seek mispriced securities with the objective to realize abnormal returns. The competition ensures that the prices will be near their fair values meaning that most managers will not beat the benchmark. Exceptional managers still might beat the average forecasts that are built into market prices and consequently construct portfolios with abnormal returns. The proponents of active management base their economic logic into Grossman and Stiglitz's (1980) perception of market efficiency. If no analyst can beat the passive strategy, investors will not be willing to pay for expensive analysis and will adopt less expensive passive strategies. As the amount of assets under active management will dry up the competition of abnormal returns decrease. In that case, the prices will no longer reflect sophisticated forecasts and profit opportunities will once again lure back to active managers. As an empirical evidence supporting active management (and on top of the previously discussed anomalies), Bodie et al. (2008, 65) mention the long streaks of abnormal returns experienced by some managers that can hardly be labelled as lucky outcomes. Secondly, they mention the amount of noise in realized rates of return which is enough to support the hypothesis that some managers can beat the market by a small, yet economically significant margin.

Several attempts have been made to measure the degree of active management and to provide insights into a fund's investment strategy. These approaches are based on easily comprehensible metrics by gathering fund information data or without relying on detailed fund-specific information at all. One of the latter ones and a traditional measure of managerial activity is tracking error (or more formally tracking error of volatility). Cremers and Petäjistö (2009) define tracking error as the time-series standard deviation of the difference between portfolio return and its benchmark index return:

$$Tracking\ Error = Stdev(r_{portfolio,t} - r_{benchmark,t}) \tag{19}$$

Thus, tracking error is measure of the additional standard deviation of the portfolio returns due to active deviations from the benchmark. An alternative to the tracking error is a simple correlation between the fund and its benchmark (Alexander & Dimitriu, 2004). It can be obtained as the r-squared term from a simple regression. Ranging between 0 and 100, the r-squared coefficient represents the percentage of a fund's movements "explained" by movements in its benchmark. More actively managed funds tend to have lower r-squared values. Other common measures in the financial literature used to indicate managerial activity are the portfolio turnover and the Active Share measure. Turnover is the ratio of the trading activity of a portfolio to the assets of the portfolio (i.e. Wermers, 2000; Dahlquist et al. 2009). Respectively, the Active Share introduced by Cremers and Petäjistö (2009) is a measure of the percentage of stock holdings in a manager's portfolio that differ from the benchmark index. Due to the limitations of this study, the first two measures are employed, since the latter ones require quite a lot of detailed, fund-specific data.

Wermers (2003) states that if some subgroups of managers have better skills than most, they would make "bets" away from the market portfolio, or from style benchmarks to take advantage of their supposed superior information. Further, the managers with superior information would deviate from these benchmarks more than a manager with only good information. Thus an issue of great interest to investors is whether fund managers that hold portfolios with substantial total volatility, or with substantial non-market volatility, outperform indexers as well as active managers with less tracking error.

When it comes to stock selection and factor timing, a small cap fund can be considered a typical example of a pure stock-picker, since it does not have any predetermined objectives to follow a strategy related to certain industries or sectors. It rather aims at selecting individual stocks within industries, and at the same time aims for high diversification across different industries. Cremers & Petäjistö (2009) note that tracking errors of small cap funds are substantially lower than for example "sector rotators" who focus on picking entire sectors and industries that are expected to outperform the broader market. This suggests that they are less active but that is an incorrect conclusion. Cremers and Petäjistö note that a diversified stock picker can be very active despite its low tracking error because the stock selection within industries can still lead to large deviations from the index portfolio even while potentially contributing for positive alphas. In contrast, a fund betting on systematic factors can generate a large tracking error without large deviations from index holdings.

3 LITERATURE REVIEW

3.1 A brief history of mutual funds

Most investors do not realize how long mutual funds have been on the financial landscape. The roots can be in fact traced back to 19^{th} century Great Britain. The Foreign and Colonial Government Trust which resembled a mutual fund was formed in London in 1868. The trust promised the "investor of modest means the same advantages as the large capitalist … by spreading the investment over a number of different stocks". The fund still trades on the London stock Exchange. Most of the early day British and American investment companies resembled today's closed-end funds. A fixed number of shares were sold and their price was determined by supply and demand. The first so-called open-end mutual fund emerged years later in 1924. The Massachusetts Investors Trust introduced a portfolio of 45 stocks and 50 000 dollars in assets. The new concepts revolutionized investing and investment companies by offering continuously new shares and redeemable shares that could be sold any time based on the current value of funds' assets. (Pozen 1998, 55). Although the first mutual fund was founded in Europe, the US market contributes overwhelmingly to the early history of mutual funds.

The stock market crash of 1929 and the Great Depression that followed prompted the government regulators to take notice of regulating the securities markets and mutual funds in particular. In 1933-1936 a series of acts were passed to protect investors. The acts required mutual funds to register with the SEC and provide a prospectus describing the fund. Guidelines for taxation, advertising and distribution rules were established. The most effective investor protection laws, enacted with strong industry support, were adopted in 1940's Investment Company Act to minimize conflicts of interest. The regulations were not only on mutual funds themselves but also their principal underwriters, directors, officers, employees and advisers. The act's core was the requirement that every fund must price its assets based on market value every day. It mandates that shareholders can redeem their shares upon anytime and that mutual fund is required to pay a price based on the next calculated net asset value of the investment portfolio within seven days after receiving the redemption request. Leverage limits and prohibitions on transactions between a fund and its manager were also imposed. A former chairman of the SEC once said, “No issuer of securities is subject to more detailed regulation than mutual funds.” (Pozen 1998, 55-56).

The mutual fund industry began to grow again when confidence in the stock market returned in the 1950s. By 1970 there were approximately 360 funds with 48 billion dollars in assets. (Fink, 2008, 63). Innovations in retirement vehicles and the arrival of new products such as money market funds and index funds boosted the industry growth dramatically. Mutual funds became a preferred investment option in certain types of retirement plans. (Pozen 1998, 56). The growth continued in 1980s and 1990’s due to a bull market for stocks and bonds until the credit crisis of 2008. Demand for equity funds generally correlates with stock market performance and lower market volatility. Net cash flows to equity funds rise when the stock markets rise and vice versa. Between 2008 and 2012 the industry faced cumulative cash outflows of $537 billion, an average of $107 billion per year in the US. A steady demand was obtained again throughout 2013 with the support of relative outperformance of equities coupled with lower stock market volatility. The industry received positive net cash flows each month except for December in the US. (2014 Investment Company Fact Book).

Although the money outflow from actively managed funds slowed significantly in 2013, the share of index-oriented investment products has grown particularly quickly. The percentage of index equity accounts for 18.4 percent (in 2013) of the equity mutual funds’ total net assets and has doubled in the US since 2000. From 2007 through 2013 ETF’s and index equity mutual funds received a new $795 billion cumulative net cash inflow from reinvested dividends, whereas outflows from equity mutual funds were $575 billion. Therefore, it can be concluded that fair share of outflows from actively managed products have gone to passive ones. (2014 Investment Company Fact Book, 2014). All in all, the industry is constantly developing the offering of new products, services and distribution channels to meet customer demands. Today’s repertory of mutual funds runs from aggressive growth stock funds, global bond funds, to single state tax-exempt money market funds to “niche” funds that specialize in tiny segments of the securities market.

3.2 Fund evaluation studies

The importance of correct fund evaluation is obvious as higher returns are being sold to investors in the form of management fees. As a result of the remarkable growth and popularity of mutual funds during the previous decades, it is hardly surprising that the topic has been widely researched. Alongside the risk-adjusted performance against a benchmark, fund evaluation studies typically concentrate on one or more other aspects of performance. Performance persistence is one of the most widely researched aspects since some investors tend to spend significant amount of time and effort studying the past performance of different opportunities when selecting mutual funds. Studies have shown mixed results in performance persistence in risk-adjusted returns, and a lot of the results depend on the applied methodology and time-period. Evidence of short term persistence has been shown stronger than long-term persistence. Generally persistence is found on up one-year holding periods at most, and it tends to fade dramatically after the first year. The general trend of the in the performance persistence studies has been towards short selection and holding periods (Pätäri, 2009). The other common aspects that have gained interest are the effects of active management, market timing abilities of fund managers, and fund style and characteristics. The actual performance compared to a benchmark, its persistence and the effect of active management most relevant topics concerning this study. Previous results from the three aspects are reported next. The chapter attempts to follow a timeline to some extent and cover the literature from different perspectives and research methodologies applied.

The fundaments of fund evaluation are based on 1960s insights on portfolio mathematics and asset pricing and were laid with the development of the Capital Asset Pricing Model. The development of which had a large influence on fund evaluation literature. The early studies and the performance measures of Treynor (1965), Sharpe (1966) and the Jensen (1968) are the foundation for many modern fund evaluations. The scholars developed methods that examine risk-adjusted performance against a benchmark portfolio.

Sharpe (1966) examined 34 open-end mutual fund during the time period 1954-1963 using his newly developed reward-to-variability ratio, the previously presented Sharpe ratio which measures the portfolios excess return over the risk free rate divided with portfolios standard deviation. According to the assumptions of CAPM all funds should settle along in line in a two-dimensional space of standard deviation and return and thus give an equal value of the ratio. The linear relationship between the rate of return and standard deviation was found clearly evident. However, results showed varying reward-to-variability ratios between funds and some funds were even dominated by others, meaning that some funds gained higher returns with the same level of risk. Altogether the funds showed inferior values compared to the Dow Jones Industrial Average which was used as a benchmark. Sharpe's conclusion was that on average the fund managers were able to construct a portfolio as good as the benchmark portfolio but after taking account of the costs, their performance fell short of the index. Performance persistence was studied by ranking funds based on the reward-to-variability ratio and analyzing their rank correlations over two 7-year periods. The results showed that performance can be imperfectly predicted based on earlier performance. This is one of the few studies supporting long-term persistence.

The seminal work of Jensen (1968) continued the saga of fund evaluation. Jensen extended the CAPM formula by adding a constant alpha representing the portfolio's excess return over CAPM, as presented earlier in this study. Jensen estimated the alphas with data set of 115 mutual funds during the time period 1945-1964. The average value of the alpha, calculated net of management costs was negative, indicating poor performance. The beliefs in forecasting abilities of the fund management industry were even more relapsed by the fact that Jensen came to same conclusion when estimating the model also gross of all management costs. Neither was there strong evidence that such forecasting abilities were possessed by any individual fund.

Ippolito (1989) was interested in the mutual fund industry as a whole and the market efficiency in capital markets when information is costly to collect and implement. He studied the performance of 143 mutual funds in the period of 1965-1984 by estimating Jensen's alpha for the funds. He reported contrary results to the previous studies. First, the risk-adjusted returns in the mutual fund industry were comparable to low cost index funds as the mutual funds were able to offset the expenses. Second, individual funds were able to produce significant positive alphas. Portfolio turnover and management fees were also found unrelated to performance. Ippolito's conclusion is that such market efficiency where security prices would reflect all available information is impossible because information is costly to obtain and thus efficient for the arbitrage function to be incomplete. He states that market efficiency should rather be understood as Grossman (1976) and Grossman and Stiglitz (1980). Grossman and Stiglitz (1980) also present evidence that informed managers are able to offset their expenses. They state that informed investors would make trades occur at different prices from full-information prices to compensate them for the cost of becoming informed. If all relevant information was already reflected in the prices, no single agent would have sufficient incentive to acquire the information on which prices are based.

The ability of prior winners to repeat their superior performance was truly triggered by Hendricks et al. (1993) and Goetzmann and Ibbotson (1994). They are among the most cited studies of mutual fund performance persistence. Hendricks et al (1993) found that performance persists in the near term but disappears when a longer horizon is used. The strongest evidence is found for one-year evaluation horizon. Their data included returns of 165 no-load growth-oriented mutual funds between 1974 and 1988. A strategy of selecting quarterly the top octile performers from last four quarters generated significantly higher returns than the average mutual fund. However, the performance was only marginally better compared to some benchmark indexes. Goetzmann and Ibbotson concluded that the phenomenon is present in both raw and risk-adjusted returns. The two studies labelled the phenomenon as "hot hands" effect. To the poor past performers, the evil counterpart of hot hands, they refer to as "icy hands". Hendricks et al. showed that poor past performance continued to be inferior in the near term. Moreover, they seemed to be more inferior than hot hands are superior. Brown and Goetzmann (1995) also document performance persistence, however occasionally subject to significant performance reversals.

Malkiel (1995) questions the preciseness of studies conducted in the 1980s and early 1990s. He argues that the results showing superior returns end existing performance persistence are subject to survivorship bias, the importance of which is shown greater than previous studies estimated. Survivorship was first documented by Brown et al. (1992). More specifically it means the problem of how to deal with dead or merged funds during the sample period of the study. Malkiel criticizes the typical methodology of using records only of funds currently existing and excluding funds that have terminated operations. This could lead to exaggerating of average performance. Malkiel utilizes a data set including returns of all US equity funds that existed between 1971 and 1991. Jensen’s alpha was applied as performance measure and the results showed that the funds tended to underperform the market, not only after management expenses but also gross of all reported expenses except load fees. However, the persistence phenomenon was documented but the evidence was weak since the phenomenon was only characterized in 1970s but not in the later period. In conclusion, Malkiel does not encourage to abandon the belief that security markets are remarkably efficient

An influential paper that somewhat contradicts the previous studies supporting performance persistence was introduced by Carhart (1997). He introduced the 4-factor asset pricing model that captures the momentum effect. Carhart attributes almost all persistence in mutual fund performance to the four factor loadings. Carhart’s primary analytical technique was to form performance decile portfolios of mutual funds on each year based on returns over the past year. The portfolios are then held for one year and monitored for any abnormal performance. If performance is persistent, funds that performed well in the past should perform well in the future, and the top decile portfolios should outperform the other portfolios. The results showed that past winners do outperform past losers. However, most of this persistence is explained by the 4-factor model, momentum effect being the biggest explanation of the results. He also states that the remaining persistence is mainly explained by fund expenses and transaction costs which are higher in the lower performance deciles. The difference in annual returns between top and bottom deciles was 8%, of which 4.6% is explained by the four factor loadings, 0.7% is explained by expense differences, and 1.0% is explained by transaction cost differences. This still leaves an unexplained return spread of 1.7%, almost all of which is attributable to the spread between the two lowest deciles. In other words, the results show that the very worst funds continue their underperformance, but finds no support for the existence of skilled or informed fund managers.

Besides a stream of literature that evaluates fund performance over time, there are also studies that evaluate fund performance across various market segments and relates performance differences to differences in efficiency across the market segments. For example Chen et al. (2000) report that growth-oriented funds earn larger alphas than income-oriented funds that specialize in value stocks that have a good history of paying dividends. The common interpretation of the results is that growth fund managers operate in a less efficient market than income fund managers and can thus add more value through active portfolio management. Chen et al. (2000) conducted the study by examining individual stock trades which is a slightly different approach from the mainstream of studies. Although, the stocks held by mutual fund do not outperform the general population of stocks, the stocks they buy have significantly higher returns than the stocks they sell. The difference was roughly 2% in the one-year holding period. They also find weak evidence of better stock-picking skill of funds with best past performance compared to funds with the worst past performance.

Some mutual funds implement mechanical portfolio strategies based on stock characteristics like book-to-market, size and momentum. These passive strategies have been demonstrated to be implemented at a substantially lower cost than more subjective strategies based on fundamental analysis. Daniel et al. (1997) applied models based on market timing and stock selection using 2500 equity funds that existed between 1975 and 1994. The objective was find out whether active investment strategies are wasting resources or outperform simpler, purely mechanical strategies. The results show that funds exhibit no characteristic market timing ability but show some selectivity ability, especially among aggressive-growth and growth funds. The evidence of the 4-factor model shows, in fact, that the average mutual fund succeeds in the mission of beating the mechanical strategy. However, difference was fairly small and approximately equal to the average management fee. The aggressive-growth and growth funds who exhibited the highest performance presumably also generate higher costs. Even stronger performance numbers were previously documented by Grinblatt and Titman (1993) with similar data, but their methodology did not control for performance due to momentum investing. Daniel et al., however, conclude that momentum investing does not entirely explain why aggressive-growth and growth funds tend to outperform other funds. Altogether, the evidence is consistent with an equilibrium, like that of Grossman and Stiglitz (1980) where informed managers are able to at least earn back their fees. On performance persistence, Daniel et al. report that stocks held by last year's best funds outperform other stocks in the following year but the hot hands phenomena found in data sets can be explained by the momentum anomaly.

Despite the fact that performance persistence in superior return has been explained by differences in common risk factors, Bollen and Busse (2005) find short-term persistence beyond momentum. Their results using high frequency daily data indicate that the phenomenon is observable using short measurement horizons. Huij & Verbeek (2007) also came up with similar results. They studied short-run performance persistence with data of more than 6400 US equity funds. They sorted the funds to rank portfolios based on their past performance and found out that the top decile of funds earns a statistically significant abnormal return of 0.26% per month. They also stated that persistence varies across investment styles and is mostly concentrated in relatively young small cap/growth funds.

The previously presented studies have focused on US domestic mutual funds but short term persistence has been found using data of international mutual funds. Droms & Walker (2001) are one of the few who have studied the phenomenon with international data. Their conclusion was that international equity funds exhibited significant performance persistence for 1-year holding periods. No persistence for 2-, 3-, or 4-year periods was found significant at any meaningful probability level.

Pätäri (2009) notes that investors are still unlikely to benefit substantially from short-run performance persistence due to increased costs of frequent rebalancing of portfolios. He also states that there is hardly any evidence that picking only the prior best performing funds would result in superior performance in the subsequent period. At best, it can increase the odds of achieving better-than-average returns in the subsequent period.

If superior skills exist, why they seem to vanish over time? Berk and Green (2004) offer a theoretical argument for lack of performance persistence. They state that open-end mutual funds face additional risk capacity constraints which arise when investors heavily allocate money to recent outperformers. These funds then grow in size and suffer from decreasing returns to scale in active management. Second, investors, at least in theory, withdraw money from underperforming funds. Benefitting from decreasing returns to active management, these funds should theoretically return to average performance levels

One of the most interesting papers considering this study is the study by Otten and Bams (2002). They employed the Carhart's 4-factor asset-pricing model to evaluate the performance of European mutual funds in five countries. The results revealed a preference for small cap funds and funds that primarily hold value stocks. Furthermore they show that small cap funds outperform their benchmark even after they have controlled for the common risk factors using the 4-factor model. In total, four out five countries (UK, France, Italy and Netherlands) delivered positive aggregate after-cost alphas. Noteworthy is that German funds underperformed even before costs. Contrary to the most US evidence the European funds seemed to be able find and implement strategies to offset their expenses and add value to the investors. The authors argue that that it could be due to smaller market importance of European funds versus the US industry. The US mutual fund industry held at time 30% of the domestic equity market where the European funds were rather a small player with a 10% share. Overall, Otten and Bams argue that market importance is inversely related outperformance. This could also provide a rationale for the superior performance of small cap funds. First of all, they represent only a niche in the European mutual fund market. Second, actively managed small cap funds represent only a fractional share of the European small cap equity market. Otten & Bams argue that since arbitrage opportunities are finite, it can hardly be expected funds to outperform their benchmark if they represent the majority of the market since they cannot outperform themselves. Additionally, the results showed that fund age and expenses are negatively related to risk-adjusted performance, while fund assets are positively related. Significant evidence of performance persistence was provided only in the UK. Furthermore, Pätäri (2000) does not find evidence of performance persistence either in the Finnish market using a sample of 14 equity funds.

In a quite recent study Fama & French (2010) state that the persistence studies have an important weakness because they rank funds based on past short-term performance. They argue that the little evidence of persistence is due to the allocation of funds to winner and loser portfolios which is largely based on noise. They also argue that if some managers earn positive alphas, they must be balanced by managers who produce negative alphas. They applied bootstrap simulations on fund returns to infer the existence of superior and inferior funds. When the performance is measured before costs, they find more inferior and superior performance in the extreme tails of the cross-section alpha estimates than would be expected if performance was just due to chance. The after-cost alpha estimates, however, suggest that only few active funds produce benchmark-adjusted expected returns that cover their costs. And even for the top percentiles, historical strong past performance is probably due to chance. Going forward, the alpha estimates for the top performers is close to zero, which is about the same as for an efficiently managed portfolio of passive funds.

3.3 Studies on the effects of managerial activity

Although all of the fund evaluation studies somehow aim to answer the question about the value of active management, some studies concentrate more specifically on the level of managerial activity. These studies usually evaluate the performance with respect to different measures of managerial activity. For example in the previously discussed study of Chen et al. (2000) the authors also examine the performance of stocks held an traded by funds with varying levels of portfolio turnover to determine whether funds trading more frequently outperform other funds. Portfolio turnover is defined as the percentage of a fund’s holdings that have changed over the past year. It gives an idea of how long a manager holds on to a stock. It is calculated by dividing fund’s total sales or purchases (controlling for changes in fund cash holdings), whichever is less, divided by fund’s average assets during the year. The definition, therefore, captures fund trading that is unrelated to investor inflows or redemption. Chen et al. conclude that high turnover funds have better stock selection skills than low turnover funds in the U.S market. Dahlquist et al. (2009) find same type of evidence from the Swedish market. Along with turnover they used commission fees of the fund (trading costs) divided by fund size as trading activity measures. They state that performance is inversely related to fees but on the other hand, more actively trading funds outperform their less active competitors. Contrary to the previous two, Wermers (2000) documents that turnover is not associated with fund performance.

Shukla (2004) also reports that the funds with highest turnover do not generate the highest excess returns. Contradict to the results of Dahlquist et al. (2009) Shukla finds a positive relationship between performance and expense ratios, suggesting that fund managers who are able to generate higher returns on their portfolios also charge higher fees. Thus, the benefits of active management do not end up to mutual fund shareholders.

Wermers (2003) later studied the cross-sectional relation between active bets made by the fund managers and the performance of funds. This bring some managers out in a somewhat flattering light and support the idea that more skilled or informed managers would deviate from the market portfolio more than their less informed colleagues. The results show a generally positive relation between the level of risk taken by the mutual funds and the performance of these funds.

In a more recent study, Cremers and Petäjistö (2009) measured the managerial activity using their newly developed Active Share measure which was briefly presented in the section 2.5 of this study. They found out that managers with high Active Share outperform their benchmark indexes, and that the measure significantly predicts future performance. They also state that Active Share is useful in identifying managers who claim to be active but whose portfolios are very similar to the benchmark portfolio. In contrast, Cremers and Petäjistö state that active management measured by tracking error does not predict higher returns and going from low to high tracking error may even hurt performance.

Are there then some characteristics that define competent managers? Chevalier and Ellison (1999) tried to answer the question and came up with somewhat interesting results. After correcting the data for differences in risk characteristics, survivorship biases, differences in expense ratios and differences in factor loadings in the four factor model, the results suggest that managers with higher SAT scores and degrees from more selective undergraduate institutions earned significantly higher returns than managers who attended less selective undergraduate institutions. Noteworthy is that some managers were able to beat the market even after expenses they charge. The results are suggestive that stock picking abilities exist in a subgroup of managers. Chevalier and Ellison propose explanations from direct benefits from better education and the differences in values of social networks different schools provide. Third suggested explanation is that it could be related to characteristics of fund companies, the people from different schools get employed. Moreover, they find evidence (even though somewhat fragile) that older managers perform worse than younger managers. This could be due to career concerns. Younger managers tend to work harder since they have a longer careers ahead of them and they might be more afraid of getting fired. The results are also consistent with the hypothesis that older managers are generally less well educated, as well as with a reverse selection effect in which skillful managers may exit the industry for other, perhaps more demanding assignments.

4 DATA AND METHODOLOGY

4.1 Data

The return data of the funds consists of monthly returns from actively managed open-ended European small cap equity funds categorized by Morningstar (Europe Smaller Companies category). Only funds denoted in Euro are included in the sample. The funds either do not pay dividends or reinvestment of all pay-outs such as dividends is assumed. The time range is from January 2008 through December 2013 with minimum length set to 24 months. The returns are net of expenses.

The funds of the sample typically invest in companies with median market capitalization, typically around two billion euros.[3] The definition of small cap, however, is not explicit and can vary over time and between brokerage houses. For example Alken, one fund included in the sample, announces that it focuses, albeit not exclusively in smaller companies with market capitalization less than 5 billion euros. Some funds include also midcaps which are considered companies with market capitalization typically less than 10 billion euros. Altogether, the funds seek long-term capital appreciation and risk-adjusted outperformance against the benchmark through active management. The funds invest in equity (and contingently in equity related securities) of companies with their headquarters, major activities, assets or other interests mainly in Europe. They also seek to benefit from the growth potential of the companies, since the target companies are usually in their somewhat early stage of business and are not considered as financially strong or as established as larger companies. As the benchmark index for fund returns MSCI Europe Small Cap Index is applied. The MSCI Europe Small Cap Index is a free float-adjusted market capitalization weighted index that is designed to measure the equity market performance of the small cap size segment. The index captures representation across 15 developed market countries in Europe. With 912 constituents, the index covers approximately 14% of the free float-adjusted market capitalization in the European equity universe.

[3] The average market capitalization of the constituents of MSCI Europe Small Cap Index is 1 207.03 USD million, median 852.32, largest 7 847.52, smallest 52.38. MSCI (2015).

The sample includes all funds that existed in the period. However, the sample is not completely free of survivorship bias, since funds with less than 24 months of data were excluded. In the Spearman rank correlation test and ranked portfolio tests that are employed considering performance persistence and the effect of managerial activity, only funds with data available from the whole sample period are included in the sample. In these cases survivorship bias is not considered to affect the results.

Logarithmic returns of monthly observations are used in the calculations because of easier statistical properties (Tsay, 2010). Log returns are defined as the natural logarithm of the simple return. Simple return r_t is defined as:

$$r_t = \frac{p_t - p_{t-1}}{p_{t-1}} \tag{20}$$

Logarithmic returns are gained from the equation:

$$r^{log} = \ln\left(1 + \frac{r_t}{100}\right) \times 100 \tag{21}$$

As a proxy for risk free rate, monthly averages of 3-month Euribor rates are used. Since monthly data of fund returns is employed and the 3-month Euribor is quoted on annual level, the annual rates are converted into a monthly level by:

$$r_f^{log} = \ln(1 + euribor3m_i)/12 \tag{22}$$

Table 1 provides monthly return characteristics of the mutual funds and the MSCI Europe Small Cap Index in excess of the risk free rate each year over the 2008 and 2013.

Table 1. Descriptive statistics for fund returns and the benchmark index.

Table presents the descriptive statistics for monthly excess returns of the mutual funds and the MSCI Europe Small Cap index over the sample period. Standard deviation, kurtosis and skewness are presented in average values. Number of funds presents the number of funds that had at least some activity in the corresponding year.

Mutual funds	2008	2009	2010	2011	2012	2013
Mean	-6,0890%	3,1375%	2,0191%	-1,6548%	1,6739%	2,0580%
Median	-4,7918%	2,9711%	1,7185%	-0,9262%	1,6622%	2,1938%
St. Dev	8,6707	5,6263	4,3308	4,7876	3,7874	2,7255
Kurtosis	-0,5043	0,9772	-0,2387	0,5850	1,3482	0,5619
Skewness	-0,6170	0,6277	-0,2646	-0,5226	-0,6886	-0,4549
Minimum	-33,653%	-12,650%	-10,665%	-19,504%	-13,330%	-10,015%
Maximum	10,891%	26,038%	11,758%	11,382%	12,241%	10,366%
No. of funds	78	82	82	82	77	67

MSCI Europe Small Cap	2008	2009	2010	2011	2012	2013
Mean	-6,4511%	3,6233%	1,9675%	-1,8626%	1,7409%	2,1966%
Median	-4,4067%	3,3896%	2,1915%	-0,9385%	1,9770%	2,4581%
St. Dev	8,4504	6,5068	4,3509	4,6533	4,0168	2,8383
Kurtosis	-0,4527	2,1382	0,1268	0,8074	3,2064	2,6004
Skewness	-0,6549	0,9434	-0,3584	-0,4275	-0,9878	-1,1850
Minimum	-22,912%	-6,4978%	-7,7346%	-11,3988%	-8,1267%	-4,7696%
Maximum	2,8010%	19,0566%	8,8242%	6,3520%	8,5765%	6,2005%

Even though some evidence contradicting of the explanatory power of CAPM is reported literature, it is reasonable to apply also the one-factor model and review the performance of European small cap funds in order to compare the results with previous studies. In order to alleviate the predicated shortcomings of CAPM the SMB and HML and MOM factors are constructed for the Fama French 3-factor model and Carhart's 4-factor model. In the construction of the size factor, logarithmic monthly returns of MSCI Europe Small Cap and Large Cap Indexes are used. Respectively, in the construction of value factor, logarithmic monthly returns from MSCI Europe Value and Growth Indexes are used. The portfolios are constructed as discussed in the second section. The momentum factor for European markets is obtained from Kenneth French's website where the risk premiums for the factors are updated on a monthly basis. Table 2 provides summary statistics for the factor portfolios. The average monthly return of SMB is 0.47%, indicating that small cap stocks have outperformed large cap stocks by 5.64 percentage points on an annual level between 2008 and 2013 in Europe. Respectively, negative average return of HML shows that growth stocks have outperformed value stocks almost by the same amount. Thirdly, past months' winner stocks have outperformed the past months' loser stocks by 7.44 percentage points on a yearly basis in the sample period. The difference can be considered quite remarkable.

Table 2. Summary statistics for the factor portfolios

This table shows the return characteristics for the variables in the 4-factor model between 2008 and 2013. The cross-correlations between each factor portfolios are presented in the last columns.

Factor portfolio	Average monthly return	St. Dev.		*Cross-Correlations*		
				rm-rf	*SMB*	*HML*
rm-rf	0,20 %	6,33 %	*rm-rf*	1		
SMB	0,47 %	2,67 %	*SMB*	0,6560	1	
HML	-0,43 %	2,67 %	*HML*	0,4515	0,0378	1
MOM	0,62 %	4,99 %	*MOM*	-05187	-0,3274	-0,7112

The alphas are estimated using a time-series regression where the alpha is the intercept term of the regression. Ordinary least squares (OLS) is used to estimate the unknown parameters.

4.1 Methodological perspective for performance persistence

In academic literature, different approaches have been applied to analyze to what extent fund performance during one period continues in the following period. The most common approaches for performance persistence are autocorrelation tests for performance measures, the Spearman rank correlation test, contingency tables, as well as ranked portfolio tests for decile as well as spread portfolios (Hendricks et al. 1993; Brown & Goetzmann, 1995; Malkiel, 1995). Most methods involve ranking or grouping funds based on their performance over the previous, so-called selection period and then forming portfolios according to the rankings (Carhart, 1997). The portfolios are then evaluated over the subsequent period (holding period). Simulations by Carpenter and Lynch (1999) indicate that ranked portfolio tests are the most effective tests for detecting performance persistence.

Simplest performance measure for portfolio formation would be cumulated raw returns but it is not an adequate measure of investment skill since they do not account for risk. For example, a growth fund might end up with the top performers in a period where growth stocks outperform value stocks, even if the manager has no skill (Carhart, 1997). In this study, the 4-factor alpha is employed as the ranking measure considering performance persistence since it is considered the most adequate measure of performance. The results are also presented based on 3-factor alpha to abstract the momentum anomaly's effect on persistence. The downside of the risk-adjusted measures is the possible estimation error in short ranking periods, when 12-month and 24 month horizons are used.

To investigate performance persistence based on fund rankings, the Spearman rank correlation test is applied. Same test is also applied to study the effect of active management. The correlation coefficient of Spearman rank is given as follows:

$$\rho_s = 1 - \frac{6 \sum D^2}{n(n^2 - 1)} \tag{23}$$

where ρ_s is the rank correlation coefficient, *D* is the difference between fund's selection period and holding period ranks and *n* is the number of funds.

The sign of the coefficient indicates the direction of association between the independent and dependent variable. The ρ will always maintain a value between one and zero. To test whether it is significantly different from zero can be tested using the t-test:

$$t = \rho \sqrt{\frac{n-2}{1-\rho^2}} \quad (24)$$

The zero hypothesis assumes that the correlation coefficient is not significantly different from zero. To show persistence in performance, the correlation coefficient of fund rankings should be positive and statistically significant.

Another methodology that is used to investigate mutual fund performance persistence are cross-sectional regressions. This method is applied e.g. Bollen & Busse (2005) and Huij & Verbeek (2007). With the cross-sectional regressions, funds' post-ranking alphas are regressed on performance estimates over the pre-ranking period:

$$Perf_{i,t} = \alpha + \beta Perf_{i,t-1} + \varepsilon_{i,t} \quad (25)$$

where $Perf_{i,t}$ is the post-ranking 3- and 4-factor alpha estimates of fund *i* and $Perf_{i,t-1}$ is funds pre-ranking performance measured by the monthly returns, α is the intercept, β is the slope coefficient and $\varepsilon_{i,t}$ is the error term. The alphas are estimated using standard OLS over 12- and 24-month periods. The cross-sectional regression is estimated for all 88 funds at the beginning of each period. Dead or non-disclosed funds are expected to earn average monthly returns when no data is available.

The null hypothesis is that performance on the subsequent period is independent of the previous performance, thus a significant loading on the slope coefficient would implicate persistence in fund returns.

5 EMPIRICAL RESULTS

5.1 Performance

5.1.1 Annual returns

Annual returns are calculated from the monthly data using geometric mean. Table 3 presents the results. First, it is remarkable that the funds showed top relative performance in 2008 which was the year of massive financial turmoil. In 2009, when the economy slightly recovered and the highest annual returns were received, the funds showed the poorest relative performance against the benchmark. Altogether, the results show quite well-matched performance between the sample of funds and the benchmark. On average, funds have outperformed the market in three out of six years. When examining the yearly abnormal returns over the benchmark further, it can be noted that the average is -0,006%, indeed indicating even performance between the funds and the benchmark index. Respectively, the majority of the funds have outperformed the benchmark in four out of six years. In 2012, however, the difference being one single fund. The outperformance percentage averages in 51% which also indicates equal performance between 2008 and 2013.

Table 3. Annual returns of mutual funds and the benchmark index

Table shows the returns of funds that had data available for the entire individual year. The number of funds is illustrated in the second column. The table also illustrates the percentage of funds that outperformed the benchmark in the particular year.

Year	n	Market Return %	Average Fund Return %	$r_i - r_m$	Outperforming funds %	min %	max %
2008	75	-6,815	-6,5003	0,3147	0,6933	-9,0638	-4,2356
2009	77	3,4411	2,9966	-0,4445	0,2468	1,7087	5,4389
2010	77	1,8638	1,9579	0,0941	0,6364	0,3412	2,9404
2011	73	-1,9651	-1,807	0,1582	0,5753	-2,7828	0,0296
2012	69	1,6664	1,6076	-0,0589	0,5072	0,5372	2,6596
2013	66	2,1597	2,0607	-0,0990	0,4091	0,8321	3,1695

5.1.2 Risk-adjusted performance

To bring more insight on the performance of funds, several risk-adjusted measures are reported in the next tables. Table 4 shows that based on Sharpe ratio the funds have slightly outperformed the MSCI Europe Small Cap Index on average. However, the values of the Modigliani measure and the Treynor ratio are in line with the idea that funds are unable to produce positive abnormal return net of expenses. From an investor's point of view, a randomly picked fund would more likely beat rather than loose against the benchmark since the majority of the 88 funds rank on the outperforming side when compared to the benchmark.

Table 4. Results for Sharpe ratio, Modigliani measure and Treynor ratio

Table reports the three risk-adjusted measures for the sample period 2008-2013. Fund average is the average of the 88 funds in the survivorship controlled sample. Percentage of the funds that have outperformed the benchmark is calculated for each of the three measures.

Measure	Benchmark	Fund Average	Difference	Outperforming funds %
Sharpe ratio	0,032	0,0375	0,0055	0,5455
Modigliani measure	0,2659	0,1866	-0,0793	0,5114
Treynor ratio	0,2024	0,1689	-0,0336	0,5341

Table 5 presents the results for the Jensen alpha and 4-factor alpha measures. First, it can be seen that the average alphas from both models are negative indicating average underperformance. Some funds examined are able to produce significant alphas. However, the 4-four factor model suggests that inferior performance is more significant than superior performance. As expected the CAPM alphas clearly exaggerate the performance of funds compared to the 4-factor alphas. The average Jensen alpha is basically zero and remarkably 49/88 funds have positive Jensen alphas. Respectively, only 39 out of 88 funds have positive 4-factor alphas. It also becomes clear that the multi-factor model has greater explanatory power compared to the one-factor model. The betas are all statistically significant and differ slightly from one another.

The results of underperformance are in line with the previous studies but the underperformance can be considered relatively low. When the alphas are converted into annual level, the rates are -0.0252% for Jensen alpha and -0.3684% for 4-factor alpha. These can be compared with the yearly fund expenses. According to 2014 Investment Company Factbook, the simple average expense ratio (the average for all equity funds offered for sale) of equity funds was 1.37% in 2013. However, investors tend to invest in funds with below average expense ratios so the asset-weighted average expense ratio for equity funds (the average shareholders actually paid) was lower, being. 0.74%. Altogether, the numbers suggest that gross of management costs, the funds would have produced a positive average alpha. The results are similar to previous findings in the sense that mutual fund managers are able to exploit active stock selection strategies but not to the extent to cover the expenses. The results can also be interpreted in the sense that efficient markets should be understood as Ippolito (1989) and Grossmann and Stigliz (1980), who concluded that information or investment analysis is costly but the investors are compensated for gathering and processing information.

The greater explanatory power of the multifactor model as compared to the one-factor model is caused by the SMB, HML and MOM who are not significant but provide some explanatory power. Concerning the SMB factor of the 4-factor model the interpretation is slightly different from usual. SMB captures the differences in returns between the smallest and largest stocks. The insignificance of the factor indicates that stocks in which the funds in the sample invest do not significantly differ size wise from those in the benchmark index. The slight negative exposure to HML factor suggest that that the funds have a preference towards growth stocks within the market. Positive exposure to MOM suggests that fund managers invest preferably in recent winner stocks.

Altogether 18 significant alphas are displayed depending on the risk level. The significant alphas likewise have a negative average but fund-specifically tilt on the positive side with CAPM. Based on the 4-factor model the significant alphas tilt to negative. Moreover, the most significant alphas are all negative. Compared to the CAPM, the 4-factor model reduces the credit that managers can claim for unexplained excess returns that occur simply because they hold a portfolio tilted towards small, value and momentum stocks.[4] There is still a debate whether the outperformance of these stocks is due to market efficiency or inefficiency. Market efficiency side suggests that the outperformance is generally explained by the excess risk that value and small cap stocks face as a result of their higher cost of capital and greater business risk. On the inefficiency side, the outperformance is explained by mispricing the value of these stocks, which provides the excess return in the long run.

Table 5. Estimation of Jensen alphas and 4-factor alphas

This table presents the summary of the CAPM and 4-factor model regressions for the sample period 2008-2013. The results are average monthly values. The table also reports the percentage of funds with positive alphas and the amount of statistically significant alphas.

CAPM		**4-factor model**		**Statistically significant alphas**	
Adjusted R-squared	0,8815	Adjusted R-squared	0,9476	Positive +	Negative -
Beta	0,9143	Beta	0,9528	CAPM	
p-value	1,96E-07	p-value	4,19E-05	10*	8*
Jensen's alpha	-0,0021%	4-factor alpha	-0,0307%	5**	4**
p-value	0,4476	p-value	0,4621	4-factor model	
Funds with positive alphas %	0,5568	Funds with positive alphas %	0,4431	7*	11*
		SMB	-0,002	4**	9**
		p-value	0,5178		4***
		HML	-0,0457		
		p-value	0,3813		
		MOM	0,0585		
		p-value	0,3223		

*** Denotes significance at 1% risk level

** Denotes significance at 5% risk level

* Denotes significance at 10% risk level

---

[4] For the robustness of the results the Fama-French 3-factor model was also estimated. The results altogether were more close to the CAPM than 4-factor model. The average monthly 3-factor alpha was -0.0453%, 50% of funds exhibited positive alphas and the adjusted r-squared was 0.8960. The distribution of significant alphas was equivalent to CAPM.

5.2. Performance persistence

The results in the previous literature showed mixed results whether the track record of a fund is related to its future performance. The results have also seemed to be dependent on the methodology and time horizon applied. Thus, the performance persistence in this study is examined using three different methodologies and time horizons of 12 and 24 months. Results are reported for the 4-factor alpha which is well-suited for ranking funds and considered to be the most valid performance measure of the ones applied in this study. In addition, to illustrate to what extent the momentum factor explains performance persistence, results for 3-factor alpha are also reported.

Table 6 and table 7 provide results when the performance is measured on a 12-month valuation horizon. First, the correlation coefficients exhibit both positive and negative values throughout the sample period generally suggesting that prior performance does not predict future performance. In the first two periods the results show positive relationship between past year's and following year's performance as illustrated by the Spearman rank correlation coefficients and the differences of the ranked portfolios. The results and significance levels are fairly similar with both methodologies across the whole sample period. Both alphas show significant persistence between 2009 and 2010. Altogether, the 3-factor alpha rankings show at least 10% significance levels in four out five intervals. As expected, the equivalent amount is lower (two) when the model that controls for momentum effect is used to calculate alpha. In table 7, the average annual alpha spread in the first two periods (2008-2010) between Prior winners and Prior losers is around 6%.

Picturing a strategy of buying last year's winners and selling last year's worst performing funds does not appear very insightful when the results from the rest of the sample period are considered. The pattern is reversal and the prior worst performing funds generate higher alphas. Altogether, the absolute values of the correlation coefficients are between 0.0868 and 0.2855. Verbally described, they can be considered quite weak. Moreover, the evidence from the t-statistics show that negative performance persistence in the last three annual periods is statistically not as significant as the positive performance persistence in the first two periods. A rational conclusion of the mixed and somewhat significant results is that the positive and negative persistence might be due to fund characteristics and market conditions rather than the skills of fund managers.

Further investigation of the Prior winners and prior losers in table 7 reveals that as investment strategies, both would beat the benchmark since the average alpha values are positive in the 2008-2013 period. However, it should be noted that the accuracy of the alphas each year is not that robust, since they are estimated from monthly data with only 12 observations per fund.

Table 6. Performance persistence for 12-month horizon using Spearman rank-correlation test

Table presents the results for performance persistence using Spearman rank correlation test calculated for 4-factor (bolded) and 3-factor alphas (italicized). Due to the nature of Spearman rank correlation test, 52 funds with data from the whole sample period were included

Selection period	Holding period	Correlation coefficent (ρ)	t-stat	p-value
2008	**2009**	**0,1117**	**(-0,7946)**	**0,2177**
		0,3596	*(2,7250)****	*0,0062*
2009	**2010**	**0,2855**	**(2,1064)****	**0,0234**
		0,2341	*(1,7026)***	*0,0514*
2010	**2011**	**-0,1639**	**(-1,1750)**	**0,1263**
		-0,1893	*(-1,3630)**	*0,0933*
2011	**2012**	**-0,1677**	**(-1,2027)**	**0,1209**
		-0,2226	*(-1,6143)**	*0,0604*
2012	**2013**	**-0,2604**	**(-1,9071)****	**0,0348**
		-0,0868	*(-0,6163)*	*0,2720*

***Denotes significance at 1% risk level

**Denotes significance at 5% risk level

*Denotes significance at 1=% risk level

Table 7. Performance persistence for 12-month horizon using winner-loser portfolios.

Table presents results for performance persistence using ranked portfolios. Two portfolios based on the past years' monthly alphas have been created. Results for 4-factor alphas are bolded. Respectively results for 3-factor alphas are italicized. 52 funds with data from the whole sample period were included. Prior Winners consists of 12 funds with the highest past year (selection period) alphas. Respectively, Prior Losers consists of those with the lowest alphas past year. The equally weighted portfolios are then held for one year (holding period). At the end of each year the portfolios are reformed. The significance of differences between the two portfolios is tested using two-sample t-test.

Selection period	Holding period	Prior winners (mean)	Prior losers (mean)	Winners-Losers	t-stat	p-value
2008	**2009**	**0,2637%**	**-0,1084%**	**0,3721%**	**-1,0578**	**0,1508**
		0,0138%	*-0,4598%*	*0,4736%*	*(2,3710)***	*0,0135*
2009	**2010**	**0,2976%**	**-0,2831%**	**0,5807%**	**(2,8490)*****	**0,0047**
		0,4297%	*-0,0737%*	*0,5034%*	*(-2,7864)****	*0,0054*
2010	**2011**	**0,2844%**	**0,5648%**	**-0,2804%**	**(-0,9103)**	**0,1863**
		0,3424%	*0,7069%*	*-0,3645%*	*(-1,1037)*	*0,1408*
2011	**2012**	**-0,0694%**	**0,1747%**	**-0,2441%**	**(-1,1592)**	**0,1294**
		-0,0431%	*0,2721%*	*-0,3152%*	*(-1,3757)**	*0,0914*
2012	**2013**	**0,3972%**	**0,6261%**	**-0,2289%**	**(-0,5833)**	**0,2828**
		0,1806%	*0,3973%*	*-0,2167%*	*(-0,7498)*	*0,2307*

***Denotes significance at 1% risk level
**Denotes significance at 5% risk level
*Denotes significance at 1=% risk level

Studies that have reported performance persistence tend to conclude that the phenomenon is short-lived and fades when longer time-horizons are used. Table 8 shows results for a 24-month selection period and 24-month holding period using the same methodology as previously. To compare the results with the 12-month results the winner and loser portfolios are formed correspondingly. Table 8 shows that the signs of the correlation coefficients and the differences between prior winners and losers correspond with the 12-month results. Prior winners generates a slightly higher return in the first period, whereas Prior Losers generates double the return compared to Prior Winners in the latter period. However, based on 3-factor alphas the portfolios generate a quite equal return in both periods. Closer look reveals that correlation coefficients are practically zero and the difference between Prior winner and Prior loser portfolios is, after all, quite minimal. None of the values are either significant. It seems that, as the time range for the selection and holding periods are assigned to 24-months, there is practically no relationship between past and future performance. Similar results were previously documented for example by Hendricks et al (1993) and Brown & Goetzmann (1995) who stated that performance persistence is fading when longer time periods are applied.

Table 8. Performance persistence for 24-month horizon using Spearman rank-correlation test and winner-loser portfolios.

First, table presents the results for performance persistence using Spearman rank correlation test calculated for monthly 4-factor (bolded) and 3-factor alphas (italicized). Additionally, two portfolios based on the past year's alphas have been created. Due to the nature of Spearman rank correlation test, 52 funds with data from the whole sample period were included. Prior Winners consists of 12 funds with the highest past year (selection period, SP) alphas. Respectively, Prior Losers consists of those with the lowest alphas past year. The equally weighted portfolios are then held for one year (holding period, HP). At the end of each year the portfolios are reformed. W-L illustrates the difference between the portfolios, significance of which is tested using two-sample t-test.

SP	HP	Correlation coefficent (ρ)	t-stat	Prior winners (mean)	Prior losers (mean)	W-L	t-stat	p-value
2008-2009	**2010-2011**	**0,0604**	**(0,4282)**	**0,0940%**	**0,0608%**	**0,0332%**	**(0,3859)**	**0,3516**
		0,0908	*(0,6577)*	*0,1104%*	*0,1019%*	*0,0084%*	*(0,0876)*	*0,4655*
2010-2011	**2011-2012**	**-0,0338**	**(-0,2392)**	**0,1232%**	**0,2617%**	**-0,1386%**	**(-0,8900)**	0,1915
		0,0807	*(0,5838)*	*0,2467%*	*0,2088%*	*0,0379%*	*(0,2205)*	*0,4138*

To provide more insight regarding performance persistence, cross-sectional regressions of performance on its lagged value are run using the two multifactor alphas as the performance measures. In contrast to previous methodology, the sample is less affected by survivorship bias and consists of 88 funds with data available from at least 24 months. Dead funds are expected to generate the average fund return. In the regressions, a statistically significant slope coefficient would implicate that past performance predicts future performance. Therefore, the results in Table 9 show no evidence of performance persistence on 12-month nor 24-month evaluation horizon since none of the slope coefficients appear to be significant. The significance of 3-factor alphas is generally higher. Altogether, the slopes of the regressions show both negative and positive values that actually do not even quite match the results obtained from Spearman rank correlation test and the winner-loser portfolios. The results are similar to Huij and Verbeek's (2007), who neither did find any significant slope coefficients for the OLS alphas although their paper supports the idea of performance persistence. However, they found differences between coefficients across fund styles and the valuation horizons. Overall, the applied methodology seems to affect the outcome of persistence studies.

Table 9. Cross-sectional regressions for performance persistence.

Table presents the results from cross-sectional regressions when the sample period is divided into 12- and 24-month selection and holding periods. At the beginning of each period the realized alphas over the subsequent 12 or 24 months are regressed on the performance over the preceding 12 or 24 months. The holding period performance is measured using logarithmic monthly excess returns. The cross-sectional regression is estimated to all 88 funds and the average of the coefficient estimates is reported for each period. The dead funds and non-emerged funds are considered to provide average monthly returns when data is not available. The results for 4-factor alpha are bolded, respectively results for 3-factor alpha italicized

12-month horizon

Selection period	Holding period	Slope	p-value	Adj. R-squared
2008	2009	**-0,0214**	**0,4412**	**0,0073**
		-0,0670	*0,3937*	*0,0076*
2009	2010	**0,1844**	**0,4691**	**0,0141**
		0,0999	*0,3608*	*0,0166*
2010	2011	**-0,0731**	**0,5617**	**0,0072**
		-0,1635	*0,4731*	*0,0094*
2011	2012	**-0,2445**	**0,4281**	**0,0087**
		-0,2396	*0,4316*	*0,0045*
2012	2013	**-0,1179**	**0,3313**	**0,0244**
		0,0801	*0,2052*	*0,0755*

24-month horizon

Selection period	Holding period	Slope	p-value	Adj. R-squared
2008 - 2009	2010 - 2011	0,1474 *0,2720*	0,4906 *0,4756*	-0,0010 *-0,0056*
2010 - 2011	2012 - 2013	0,0535 *-0,0031*	0,4000 *0,3447*	0,0146 *0,0079*

5.3. The effect of active management

The previous results showed that MSCI Europe Small Cap Index performed better than an average fund. However, active equity managers can attempt to outperform the market only by taking positions that are different from the benchmark. It has been argued that fund managers have an incentive to gain returns that are at least similar to the benchmark index. Thus, they might hold portfolios that are strongly correlated to the benchmark but still call themselves active to justify higher management fees. In this study, the level of active management is measured using tracking error and the R-squared obtained from the 4-factor model. R-squared of the 4-factor model represents the percentage of fund's movements that is not explained by market movements or common strategies of size, value and momentum investing. Thus a lower R-squared indicates stronger deviation from the benchmark. In the first stage, the relationship between active management and performance is studied using Spearman rank correlation test and in the second stage the funds are ranked into top, bottom and quintile portfolios based on their level of activity.

Regardless of the previous uninspiring results of the average fund manager, results in Table 10 somewhat suggest that managers with superior information on stock values deviate the benchmark more than managers with only good information. Furthermore, some fund managers have been able to take advantage of their superior information and have been able to make successful "bets" away from the market portfolio. In general, there is a positive correlation between tracking error and all of the performance measures which are cumulative returns, Sharpe ratio, Treynor ratio, Modigliani measure, Jensen alpha, 3-factor alpha and 4-factor alpha.

The absolute values of the correlation coefficients do not seem to deviate largely between variables and are between 0.20 and 0.23. In terms of the strength, the correlation can be described "weak" following the general guideline presented earlier. All of the correlation coefficients are significant at 10% risk level. On the other hand, when the funds are ranked by their R-squared, there seems to be no relationship between the variables. The coefficients are generally close to zero and insignificant.

Table 10. Spearman rank correlation between managerial activity and fund performance.

This table provides the monotonic relationship between the level of active management and six different performance measures between 2008 and 2013. In terms of activeness, the funds are ranked by tracking error and R-Squared obtained from the 4-factor model. The significance of the rank correlation coefficient is determined using Student's t-test. 54 funds with data available from the whole sample period are included.

Tracking Error

Performance measure	Correlation coefficient (ρ)	t-stat	p-value
Cumulative returns	0,2003	(1,4457)*	0,0771
Sharpe ratio	0,2093	(1,5135)*	0,0681
Treynor ratio	0,2188	(1,5852)*	0,0595
Modigliani measure	0,2165	(1,5678)*	0,0615
Jensen alpha	0,2289	(1,6627)*	0,0512
3-factor alpha	0,2033	(1,4680)*	0,0741
4-factor alpha	0,2691	(2,0146)**	0,0246

R-Squared

Performance measure	Correlation coefficient (ρ)	t-stat	p-value
Cumulative returns	0,0080	(0,0568)	0,4774
Sharpe ratio	-0,0102	(-0,0720)	0,4715
Treynor ratio	0,0154	(0,1086)	0,4570
Modigliani measure	-0,0010	(-0,0051)	0,4980
Jensen alpha	0,0200	(0,1415)	0,4440
3-factor alpha	0,0600	(0,4247)	0,3364
4-factor alpha	0,0851	(0,6041)	0,2742

*Denotes significance at 10% risk level

**Denotes significance at 5% risk level

To gain more profound understanding of active management's effect on performance, top and bottom portfolios are formed based on their level of tracking error and R-squared. The results in Table 11 are in line with the ones Table 10. They show that funds that exhibited the highest tracking error over the sample period 2008-2013 perform better than the ones with lowest tracking error. The performance of the Top-12 portfolio is superior compared to the Bottom-12 portfolio. The two sample t-tests for portfolio means show that the difference between the top and bottom portfolios is statistically significant at 10% risk level for all of the performance measures (except for cumulative returns of which the p-value is marginally higher than 10%). It is also remarkable that the Top-12 portfolio also outperforms the benchmark based on all of the measures (benchmark results in table 4). Measured by 4-factor alpha, the most active funds outperform the market 0.83% per year and the annual spread between top and bottom portfolios is 1.84%. Although tracking error might not be the most appropriate measure of active management, the results suggest that investors should clearly avoid (or at least should have avoided) small cap funds with low tracking error and favor the funds with high tracking error.

The quintile portfolios illustrate the relation between tracking error and fund performance further. Indeed, when moving from the highest tracking error quintile to the lowest, the abnormal returns measured by the three alpha measures constantly decrease as the tracking error decreases. Similar results, can be seen based on the other performance measures as well. The differences between highest and lowest quintiles is significant at 10% risk level based on all risk-adjusted performance measures. Furthermore, the quintile portfolios also illustrate the differences in asset pricing models. Measured by Jensen's alpha, only the lowest quintile underperforms, whereas measured by 4-factor alpha, only the first quintile is able to beat the benchmark. The results somewhat alike Cremers and Petäjistö's (2009) whose results also support the idea that more active funds perform better than less active funds and their benchmark when the level of activity is measured by Active Share. However, the contradicting issue is that they did not find evidence that active management measured by tracking error would predict performance.

Table 11. Performance comparison based on tracking error.

This table presents the performance measures from 2008-2013 when the funds (N=54) are sorted by their tracking error. The Top-12 portfolio consists of 12 funds with the highest tracking error and Bottom-12 consists of 12 funds with the lowest tracking error. The significance of differences between the two portfolios is tested using two-sample t-test and the results reported in the last columns. Similarly, the funds are also ranked into quintile portfolios which consist of 11 funds, except Low which consists of 10 funds. Only funds with data available from the whole sample period are included.

	Top 12 (Mean)	Bottom 12 (Mean)	Difference	Significance of difference	
Tracking Error	3,464	1,5817		t-stat	p-value
Cumulative returns	0,1345%	-0,001%	0,1344%	(-1,314)	0,1012
Sharpe ratio	0,0525	0,0311	0,0214	(1,4637)*	0,0813
Modigliani measure	0,3738	0,2536	0,1202	(1,4855)*	0,0779
Treynor ratio	0,3566	0,2029	0,1535	(1,5390)*	0,0717
Jensen alpha	0,1275%	0,0016%	0,1259%	(1,5340)*	0,0689
3-Factor alpha	0,0846%	0,0509%	0,1355%	(1,4683)*	0,0807
4-factor alpha	0,0690%	-0,0842%	0,1532%	(1,5862)*	0,0668

	Quintile portfolios					Significance of High vs. Low	
Tracking error	High	2	3	4	Low	t-stat	p-value
Cumulative returns	0,0990%	0,0358%	0,0316%	0,1684%	-0,0266%	(1,2352)	0,1155
Sharpe ratio	0,0505	0,0400	0,0411	0,0401	0,0267	(1,3654)*	0,0936
M2	0,3632	0,3024	0,3096	0,3095	0,2251	(1,4155)*	0,0861
Treynor ratio	0,3446	0,3024	0,3096	0,3095	0,2251	(1,4392)*	0,0828
Jensen alpha	0,1163%	0,0519%	0,0511%	0,0533%	-0,0260%	(1,4529)*	0,0809
3-Factor alpha	0,0756%	0,0091%	0,0071%	-0,0302%	-0,0748%	(1,3374)*	0,0981
4-factor alpha	0,0608%	-0,0075%	-0,0175%	-0,0560%	-0,1105%	(1,4860)*	0,0764

*Denotes significance at 10% risk level

Table 12 replicates the previous analysis with the exception that the portfolios are formed using R-squared. Previously, using Spearman rank correlation test, R-squared did not appear to affect the performance measures. Using this approach, the top-12 funds with the lowest R-squared seem to outperform the funds with highest R-squared based on all of the performance measures. Similarly to previous results, the Top-12 portfolio also beats the benchmark based on all of the performance measures and produces an annualized 4-factor alpha of 1.4%. The annual 4-factor alpha spread between Top and Bottom portfolios is 2.13%. The differences in performance measures between the two portfolios are statistically significant at 5% risk level with both multifactor alphas. Altogether, the results using R-squared are not as robust across the different performance measures compared to the corresponding results using tracking error. However, the multifactor alphas show stronger significance. Quintile portfolios also show that the abnormal returns are concentrated in the funds with lowest R-squared but the pattern of decreasing abnormal returns is not quite clear as it was using tracking error. The other performance measures also show somewhat greater values in the lowest r-squared quintiles. However, the results are not significant. But altogether, the results suggest that investors should favor funds with low R-squared levels.

Table 12. Performance comparison based on R-squared.

Table presents the performance measures from 2008-2013 when the funds (N=54) are sorted by R-Squared obtained from the 4-factor model. The Top 12 portfolio consists of 12 funds with the lowest R-Squared and Bottom 12 consists of 12 funds with the highest R-Squared. The significance of differences between the two portfolios is tested using two-sample t-test and the results reported in the last column. The bottom rows show the performance measured by 4-factor alpha when the 54 funds are ranked into quintiles. Quintiles consist of 11 funds, except High which consists of 10 funds. Only funds with data available from the whole sample period are included.

	Top 12 (Mean)	Bottom 12 (Mean)	Difference	Significance of difference	
R-squared	0,9171	0,9872		t-stat	p-value
Cumulative return	0,1129%	0,0104%	0,1026%	(1,1496)	0,1336
Sharpe ratio	0,0500	0,0329	0,0171	(1,0854)	0,1469
Modigliani measure	0,3529	0,2609	0,0920	(1,0300)	0,1592
Treynor ratio	0,3458	0,2117	0,1341	(1,2413)	0,1168
Jensen alpha	0,1194%	0,0095%	0,1099%	(1,2384)	0,1167
3-Factor alpha	0,1399%	-0,0184%	0,1583%	(1,7945)**	0,0448
4-factor alpha	0,1238%	-0,0538%	0,1776%	(1,9625)**	0,0327

	Quintile portfolios					Significance of High vs. Low	
R-squared	Low	2	3	4	High	t-stat	p-value
Cumulative return	0,1214%	-0,0381%	-0,0081%	-0,1021%	0,0423%	(1,0863)	0,1451
Sharpe ratio	0,0515	0,0311	0,0339	0,0445	0,0386	(1,0407)	0,1552
M2	0,3608	0,2418	0,2628	0,3569	0,2937	(0,9917)	0,1666
Treynor ratio	0,3567	0,2418	0,2628	0,3569	0,2937	(1,1946)	0,1231
Jensen alpha	0,1283%	-0,0147%	0,0068%	0,0907%	0,0417%	(1,1845)	0,1250
3-Factor alpha	0,1555%	-0,1012%	-0,0719%	0,0037%	0,0083%	(1,8552)**	0,0392
4-factor alpha	0,1358%	-0,1314%	-0,0927%	-0,0077%	-0,0270%	(1,9398)**	0,0333

*Denotes significance at 10% risk level

**Denotes significance at 5% risk level

6 CONCLUSIONS

This thesis examined the risk-adjusted performance of European small cap equity funds from the beginning of 2008 until the end of 2013. The thesis also addresses the issue of persistence in mutual fund performance emphasizing 12-month and 24-month measurement periods. Thirdly, the relationship between the activeness of fund managers and fund performance was investigated. In particular, the objective was to determine whether funds that differ from benchmark index are also rewarded by higher levels of returns. Overall, the aim was to investigate whether the results from previous literature also hold for funds investing in smaller companies. Small cap stocks are sometimes considered risky, sometimes even fraudulent and lacking in quality demanded by investors. Certainly, these are valid concerns, but small cap stocks are also said to have operational advantages, such as lower analyst coverage, large growth potential and perceived illiquidity of which active fund managers could take advantage of.

The performance was evaluated using annual returns and several traditional risk-adjusted performance measures. The employed measures were the Sharpe ratio, the Treynor ratio, the Modigliani measure, the Jensen alpha and 3- and 4-factor alphas calculated net of management fees. The evidence from the sample period was in quite in line with the previous literature. Based on plain annual returns and Sharpe ratio, the average performance of funds was equal to the market portfolio. However, the other risk-adjusted performance measures showed that on average the funds were inferior compared to their benchmark index. A group of studies and scholars suggest that average underperformance level should be negative by about the amount the fund expenses (e.g. Fama & French 2010). However, the results of this study show that the underperformance was relatively low and on average the funds were able to earn back a significant amount of their expenses. Similar results have been previously presented for example Wermers (2000) and Grinblatt and Titman (1989). In addition, when examining the performance of funds individually, the majority of funds exhibited superior performance compared to benchmark (except on the basis of 4-factor alpha). This suggests that poorly performed funds are more inferior than funds with good performance are superior. When the performance was evaluated on the basis of 4-factor alphas, the majority of funds had negative alphas along with the negative average alpha. Some funds were able to produce significant after-cost alphas but generally the significant alphas were tilted more towards the negative ones. These results also suggested that inferior performance is more significant than superior performance.

Altogether the evidence shows that fund managers are able to add value to the investors but not to the extent that fees are covered. It is also evident that fund performance is highly dependent on the performance metrics employed. The average monthly CAPM alphas were practically zero, whereas the multifactor alphas showed more inferior performance. Investors should clearly pay attention to different evaluation methodologies. Positive CAPM alpha is not necessarily a proof of abnormal performance. It can rather be caused by exposures to size, value and momentum factors which investors can capture cheaply via index funds.

When it comes to performance persistence, the results were quite mixed but it can be concluded that persistence depends on the methodology used of which Pätäri (2009) states that it is common in performance persistence studies. The persistence was examined using the Spearman rank correlation test and cross-sectional regressions in which the realized alphas were regressed on the returns in the preceding period. Thirdly, fund portfolios were constructed based on prior performance to compare the differences. To abstract the impact of the momentum effect, the results were reported for both 3- and 4-factor alphas. Not surprisingly, the evidence was similar to e.g. Carhart's (1997) and the persistence was weaker after controlling for the momentum effect. The cross-sectional regressions provided no significant evidence of performance persistence. Using the other two methodologies the results showed significant negative and or positive performance persistence which is more likely caused by fund characteristics and market conditions rather than abilities of fund managers. The evidence of persistence was also stronger for shorter investment horizons as could be expected by the previous results (e.g. Henricks et al. 1993; Droms & Walker, 2001).

Interestingly, the results from prior winner and prior loser portfolios suggest that investors may generate superior returns by a performance-chasing strategy. Furthermore, investors would earn superior returns either by investing in past years' best- or worst-performing funds, since the both portfolios generated positive average alphas in the sample period. It should be noted that the result could be caused by luck. One should also take into account the presumable impreciseness of the annual alphas estimated on the basis of 12 monthly observations. It would be of interest to study the phenomenon and the overall performance persistence of small cap funds with a longer sample period and higher frequency data.

Finally, the results showed that managerial activity and deviation from the benchmark portfolio contribute positively to performance. Funds with the highest tracking error levels and funds that exhibited the lowest correlation with the benchmark produced significantly higher returns than their opposite rivals. Moreover, the portfolios constructed from 12 funds with the highest levels of activity were able to beat the benchmark index quite significantly. The results support the idea of Wermers (2003) that more skilled and informed fund managers would deviate their portfolios more from the benchmark index than fund managers with only good information. Apparently, they are also able to take advantage of these skills. Lower R-squared levels also seemed to have a positive effect on performance, especially on the basis of the two multifactor alphas. On the basis of 3- and 4-factor alpha higher alphas were concentrated on the funds with low r-squared levels. Respectively, inferior performance was shown in the funds with high r-squared levels. The difference these portfolios was also found statistically significant.

When the managerial activity was measured by tracking error the results were quite robust and quite identical on the basis all performance measures employed. The results somewhat contradict the previous results by Cremers and Petäjistö (2009). This raises a question, whether tracking error should be considered as a measure of risk. One individual could argue that it is not the best measure of risk, because it looks at the portfolio returns relative to benchmark rather than looking at variability in portfolio returns. A fund with high tracking error is not expected to follow the benchmark closely, and thus, could generally be considered risky, but does that tell anything about how much an investor can expect to gain or lose at any given trading day? However, individually both approaches, tracking error and the correlation with the benchmark, can be seen as quite rough measures of activity.

The questions addressed in this thesis have been asked number of times before and have generated a great deal of controversy. This thesis contributes to previous literature by concluding that, on average, funds that invest in smaller companies loose to their benchmark, but some funds can systematically pick stocks that allow them to earn back a significant fraction of the fees and expenses that they charge or even more. The competition among fund managers is bound to drive market prices to near-efficient levels. For the prices to remain efficient, decent profits to diligent and active managers should be a rule rather than an exception. The main focus for future research could be in identifying these types of funds and fund managers. The discussion continues whether it is rational to invest in actively managed portfolios and believe that the manager has the ability to continuously outperform the market through successful prediction of security prices and the ability of mitigating the unsystematic risk through efficient diversification.

REFERENCES

2014 Investment Company Fact Book, 2014. Investment Company Institute. <http://www.icifactbook.org/fb_ch2.html#index> Retrieved 10.2.2015.

Alexander, C., Dimitriu, A., 2004, Equity indexing: Optimize your passive investments, *Quantitative Finance* 4, C30‑C33.

Banz, R., 1981. The relationship between return and market value of common stocks*. Journal of Financial Economics* 9, pp. 3-18.

Berk, J., Green, R., 2004. Mutual fund flows and performance in rational markets, *Journal of Political Economy*, vol. 112, no. 6, pp. 1269-1295.

Bollen, N., Busse, J., 2005. Short-term persistence in mutual fund performance. *Review of Financial Studies* 18, pp. 569-597.

Bodie, Z., Kane, A., Marcus, A., 2008. Essentials of Investments – 7th edition*.* McGraw-Hill/Irwin, New York.

Brown, S., Goetzmann, W., Ibbotson, R., Ross, R., 1992. Survivorship in performance studies. *Review of Financial Studies* 5, pp. 553-580

Brown, S., Goetzmann, W., 1995. Performance persistence*. Journal of Finance* 61, pp. 1869-1886.

Carhart, M., 1997. On persistence in mutual fund performance. The Journal of Finance, vol. 52, no. 1, pp. 57-82.

Carpenter, J., Lynch, W., 1999. Survivorship bias and attrition effects in measures of performance persistence. *Journal of Financial Economics* 54, pp. 337-374.

Chen, H., Jegadeesh, N., Wermers, R., 2000. The value of active mutual fund management: an examination of the stockholdings and trades of fund managers. *Journal of Financial and Quantitative Analysis*, vol. 35, no. 3, pp. 343-368.

Chevalier, J., Ellison, G., 1999. Are some mutual fund managers better than other? Cross-sectional patterns in behavior and performance. *Journal of Finance*, vol. 54, no. 3, pp. 875-899.

Cremers K., Petäjistö A., 2009. How active is your fund manager? A new measure that predicts performance*. The Review of Financial Studies*, vol. 22 (9), pp. 3329-3365.

Dahlquist, M., Engström, S., Söderlind, P., 2009. Performance and characteristics of Swedish mutual funds. *The Journal of Financial and Quantitative Analysis*, vol. 35, no. 3, pp. 409-423.

Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997. Evidence on the characteristics of cross-sectional variation in stock returns. *Journal of Finance* 52, pp. 1-33.

Droms, W., Walker, D., 2001. Performance persistence of international mutual funds. *Global Finance Journal* 12, pp. 237-248.

EFAMA 2013. European fund and asset management association. Asset management in Europe: Facts and figures. 6th annual review, June 2013.

Fama, Eugene F. 1998 "Market Efficiency, Long-Term Returns, and Behavioral Finance*." Journal of Financial Economics* 49, no. 3, pp. 283–306.

Fama, E., 1970. Efficient capital markets: a review of theory and empirical work. *The Journal of Finance,* vol. 25, no.2, pp. 383-417.

Fama, E., French, K., 1992. The cross-section of expected stock returns. *Journal of Finance* 47, pp. 427-465.

Fama, E., French, K., 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33, pp. 3-56.

Fama, E., French, K., 1996. Multifactor explanations of asset pricing anomalies. *Journal of Finance* 50, pp. 131-155.

Fama, E., French, K., 2010. Luck versus skill in the cross-section of mutual fund returns. *The Journal of Finance,* vol. LXV, no. 5, pp. 1915-1947.

French, K., 2008. Presidential address: the cost of active investing. *Journal of Finance* 63, pp. 1537-1573.

Fink, M., 2008. The Rise of Mutual Funds. Oxford University Press, New York.

Goetzmann, W., Ibbotson, R., 1994. Do winners repeat? Patterns in mutual fund behavior. *Journal of Portfolio Management* 20, pp. 9-18.

Grinblatt, M., Titman, S., 1993. Performance measurement without benchmarks: an examination of mutual fund returns*. Journal of Business,* vol*.* 66, pp. 47-68.

Grinblatt, M., Titman, S., 1989. Mutual fund performance: an analysis of quarterly portfolio holdings. *Journal of Business,* vol. 2, pp. 393-421.

Grossman, S., 1976. On the efficiency of competitive stock markets where trades have diverse information. *The Journal of Finance*, vol. 31 (2), pp. 573-585.

Grossman, S., Stiglitz, J., 1980. On the impossibility of informationally efficient markets. *The American Economic Review*, vol. 70 (3), pp. 393-408.

Hendricks, D., Patel, J., Zeckhauser, R., 1993. Hot hands in mutual funds: short-run persistence of relative performance. *Journal of Finance* 48, pp. 93-130.

Huij, J., Verbeek, M., 2007, Cross-sectional learning and short-run persistence in mutual mutual fund performance*. Journal of Banking & Finance* 31, pp. 973-997.

Ippolito, R. 1989. Efficiency with costly information: a study of mutual performance, 1965-1984. *The Quarterly Journal of Economics*, vol. 104. no. 1, pp. 1-23.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: implications for stock market efficiency. *Journal of Finance,* vol. 48, no. 1, pp. 65–91.

Jensen, M., 1968. The performance of mutual funds in the period 1945-1964. *Journal of Finance*, vol. 23, no. 2, 389–416.

Keim, D., 2008. Financial market anomalies, in Durlauf, L. and Blume, L., ed.: The New Palgrave Dictionary of Economics Online. Palgrave Macmillan. New York.

Lintner, J., (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The Review of Economics and Statistics*, vol. 47 (1), pp. 77-91.

Lo, A., 2008. Where do alphas come from? A new measure of the value of active investment management. *Journal of Investment Management* 6, pp. 1-29.

Malkiel, B., 2003. The Efficient Market Hypothesis and its critics. *Journal of Economic Perspectives*, vol. 17 (1), pp. 59-82.

Malkiel, B., 1995. Returns from investing in equity mutual funds 1971 to 1991. *The Journal of Finance*, vol. 50 (2), pp. 549-572.

Malkiel, B., 1973. A random walk down Wall Street. W.W. Norton & Company Inc., New York.

Markowitz, H., 1952. Portfolio selection. *The Journal of Finance*, vol. 7 (1), pp. 77-91.

Mossin, J., 1966. Equilibrium in a capital asset market. *Econometrica*, vol. 34 (4), pp. 768-783.

MSCI, 2015. MSCI Europe Small Cap Index Fact Sheet. MSCI Inc. <http://www.msci.com/resources/factsheets/index_fact_sheet/msci-europe-small-cap-index.pdf> Retrieved 17.2.2015.

Modigliani, F., Modigliani, L., 1997. Risk-adjusted performance. *Journal of Portfolio Management*, vol. 23 (2), pp. 45-54.

Otten, R., Bams, D., 2002. European mutual fund performance. *European Financial Management*, vol. 8, No. 1, pp. 75-101.

Pozen, R., 1998. The mutual fund business. The MIT Press, London.

Puttonen, V., Repo, E., 2006. Miten sijoitan rahastoihin? WSOY. Second edition.

Pätäri, E., 2009. Do hot hands warm the mutual fund investor? The myth of performance persistence phenomenon. *International Research Journal of Finance and Economics* 34, pp. 118-139.

Pätäri, E., 2000. Essays on portfolio performance measurement. Lappeenranta University of Technology, Acta Universitatis Lappeenrantaensis, no. 106.

Roll, R., 1977 A critique of the asset pricing theory's tests part I: on past and potential testability of the theory. *Journal of Financial Economics* 4 (2), pp. 129–176.

Schwert, G., 2003. Anomalies and market efficiency, in G. Constantinides, M. Harris and R. Stulz, ed.: Handbook of Economics and Finance, no. 2 pp. 939-974. Elsevier. Amsterdam,

Sharpe, W., 1966. Mutual fund performance. *Journal of Business*, vol. 39, no. 1, 119-138.

Sharpe, W., 1964. Capital asset prices: a theory of market equilibrium under conditions of risk. *The Journal of Finance,* vol. 19 (3), 425-442.

Shukla, R., 2004. The value of active portfolio management. *Journal of Economics and Business* 56, pp. 331-346.

Treynor, J., 1965. How to rate management of investment funds. *Harvard Business Review*, vol. 43, no. 1, 63-75.

Tsay, R., 2010. Analysis of Financial Time Series. 3rd edition. John Wiley & Sons, Inc., Hoboken, New Jersey.

Vishwanath S., Khrisnamurti C., 2009. Investment Management. A Modern Guide to Security Analysis and Stock Selection. Springer, Berlin.

Wermers, R., 2003. Are mutual fund shareholders compensated for active management “bets”? Working Paper, March 2003.

Wermers, R., 2000. Mutual fund performance: An empirical decomposition into stock-picking talent, style, transaction costs, and expenses. *Journal of Finance,* vol. LV, No. 4. pp. 1655-1695.