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# PREDICTION OF ACTIVELY MANAGED FUND ALPHA USING STOCK MARKET EFFICIENCY

Master's Thesis

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I have written this master's thesis independently. All viewpoints of other authors, literary sources and data from elsewhere used for writing this paper have been referenced.

**Abstract**

The decision for an investor between an actively managed and a passive index equity fund may seem marginal, but it can have a substantial impact on long-term returns. Prior research has examined whether informational efficiency affects investing and whether active fund excess return is attributed to fund manager luck or skill. To fill the research gap between these two avenues of research and provide a tool for an informed decision between funds, this thesis aims to ascertain whether stock market informational efficiency can be used to predict active fund alpha. This thesis uses two empirical models, which show that informational efficiency is a statistically significant predictor of fund returns, and it moderates the relationship between active fund alpha and the market risk premium. These findings fill the gap in the literature and provide a framework for investors to make a better-informed decision between equity funds.

Subject terms: behavioural finance, financial models, financial instruments, stock exchange
CERCS: S180, S181

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# Introduction

The first decision an investor encounters when deciding between equity funds is whether to invest in a fund that is actively or passively managed. Although both invest in the same universe of stocks, the long-term return between these may diverge significantly. This means that it is important to choose the appropriate tools to make an informed decision. While traditional tools in fund evaluation, such as the Capital Asset Pricing Model, are based on examining past returns, this thesis proposes the use of stock price informational efficiency to predict whether active management can increase long-term returns.

The informationally efficient stock market concept originates from the research of Fama (1970), who proposed the Efficient Market Hypothesis (EMH), which states that arbitrage by rational investors makes stock prices informationally efficient in the long-term. In this context, informational efficiency implies that stock prices reflect all available information. Arbitrage refers to individuals allocating resources to discover pricing anomalies and trading on them to earn returns in excess of the market average. This excess return (alpha) is compensation for participating in true price discovery by removing anomalies. By participating in arbitrage, investors move stock prices towards their fair price over time, which ensures that stock markets stay informationally efficient in aggregate. EMH further estimates that in an efficient market, no investor can expect to outperform the market in the long-term after accounting for search costs. This, however, contradicts the substantial assets under management (AUM) of actively managed funds, motivating further research into the relationship between market efficiency and active fund alpha, and how this can be used for a more-informed decision between funds. Research into this is especially relevant as the AUM of actively and passively managed funds have recently reached parity, meaning that half of all capital invested into equity funds goes to one of the two fund structures.

Further examination of EMH has led to the concept that informational efficiency of stock markets is dynamic over time and changes according to external factors, prompting the adoption of the Adaptive Markets Hypothesis (AMH) by Lo (2004). It states that investor rationality and macroeconomic factors change how informational stock prices are over time. In the context of this thesis, this means that fund manager skill is dependent on the relative informational efficiency of stock prices at a certain period or in a certain region, meaning it is necessary to research the relationship between informational efficiency and active fund alpha.

While previous research into active fund manager skill is largely based on identifying whether alpha is down to luck or skill, using efficiency may explain how to better predict future performance, and help fill the research gap between efficiency and active alpha. Thus, the research aim for this thesis is to fill this gap in the literature by connecting research into market efficiency and the decision between funds by answering whether stock market informational efficiency helps predict active fund alpha.

In order to address this research aim, this thesis utilises two empirical models to estimate whether stock market informational efficiency of the stock market can predict actively managed fund alpha. This thesis utilises quarterly returns from 2011-2024 for 82 equity funds in 12 regions that constitute around 89% of the MSCI World index. The IMF-World Bank market efficiency index is used as a proxy for stock market informational efficiency. The first model uses net returns of both active and passive funds to estimate the linear relationship between stock market informational efficiency and returns, controlling for market characteristics. The second model evaluates whether informational efficiency predicts the relationship between active fund alpha and the market risk premium. This relationship is interpreted as the extent to which fund managers manage to arbitrage stock price anomalies. The model results indicate that informational efficiency is a statistically significant predictor of returns and predicts how the relationship between the market risk premium and active fund alpha varies depending on the level of informational efficiency across regions and over time. This implies that local informational efficiency can be used as a reliable predictor of active fund alpha sensitivity to the market risk premium. In this manner, this thesis connects previous research on market efficiency and active fund performance to suggest a new instrument for making a better-informed decision between an active and a passive fund.

The thesis structure is as follows: Chapter one introduces previous research and contextualises it within the research gap and the research aim. Chapter two offers a critical overview of the chosen empirical methodology and dataset. Chapter three introduces and discusses the economic significance of the results. Chapter four concludes.

## 1. Literature review

This chapter synthesises existing research on stock market efficiency and the persistence of active fund alpha, evaluating the existing research gap between the two that may provide an insight into the decision between an active and a passive equity fund. The chapter is divided into three subchapters that analyse previous research on informational efficiency, how to measure this over time and across regions, and what affects the alpha of active funds.

### 1.1. Stock Market Efficiency

To understand the relationship between informational efficiency and the decision to allocate assets between actively and passively managed equity funds, it is first important to define the term efficient. For this purpose, this subchapter leans on the work of Fama (1965, 1970) in the explanation of the Efficient Market Hypothesis and on Lo (2004, 2012) and Malkiel (2003) in their criticism of this hypothesis.

First[1] explained by Fama (1970), the Efficient Market Hypothesis (EMH) states that markets are informationally efficient in the long-term, meaning stock prices reflect all information because individuals taking part in arbitrage trade away mispricings. EMH is further divided into three relative levels of efficiency: 1) weak-form, where stock prices reflect all information from past returns, 2) semi-strong form, where all public information is priced in and, 3) strong-form, where all information is priced in. According to Fama, active investors are incentivised to participate in arbitrage because of the trade-off where they are compensated with alpha for the costs incurred in finding mispricings. This model of arbitrage follows the *wisdom of the crowds* theory by stating that the mean trading by investors nudges stock prices towards their fair values. Following EMH, arbitrage return cannot be greater than the market return in the long-term after accounting for the cost of price discovery. Jensen (1978) offers a simplified version of this, saying that in efficient markets, the marginal benefit from arbitrage cannot exceed the marginal cost. Fama and French (2009) further found that the alpha of active stock pickers is close to zero before fees, supporting EMH in finding that the average investor cannot outperform the market.

While it is impossible for markets to be strong-form efficient, stock markets have still been found to be efficient enough for EMH to hold under most observations as confirmed by Fama (1970) and Asness (2024). The Grossman and Stiglitz (1980) paradox has been used to explain that markets cannot be perfectly efficient as transaction fees and the high cost for price discovery mean it is impossible to arbitrage away all mispricings. This is in part because it is increasingly more difficult for asset managers to arbitrage smaller mispricings as

[1] Based on the earlier work of Bachelier (1900), who was the first to describe the *random walk* theory in which stock prices behave in a random pattern, later adapted for the Black-Scholes option pricing model

the marginal alpha decreases, but costs do not. Gârleanu and Pedersen (2018) support this by arguing that markets could not function if they are strong-form efficient because investors would not be compensated enough for arbitrage. Patra and Hiremath (2022) have deduced that if markets were strong-form efficient, then active investing would be unnecessary as there would be no pricing anomalies to arbitrage.

Later being awarded the Nobel Memorial Prize in Economics for discussing the existence of market efficiency, Shiller (1990) argued that short-term pricing dislocations and financial bubbles mean markets cannot be even weak-form efficient (Liew, 2014). This is because these cases prove that investors wrongly estimate the likelihood of future events. Pedersen (2018) has further used the existence of informed active fund managers who use such mispricings to earn alpha as proof that EMH does not hold. This argument has been refuted by Malkiel (2003), who argues that if mispricings were examples that markets cannot be efficient, then asset managers would consistently outperform their benchmarks as these anomalies would be predictable opportunities for arbitrage. The fact that these short-term anomalies do not last in the long-term has been used as proof by Carhart (1997) and Berk and Green (2004) that weak-form efficiency does hold. This is supported by Schwert (2002), who found that published mispricings in informationally efficient markets are quickly arbitraged away by investors chasing alpha, keeping prices efficient in aggregate. Schwert further found that the largest factor preventing the immediate arbitrage of these opportunities in less efficient markets is higher trading fees.

The consistent elimination of these price anomalies support Fama (1970) in proving markets are efficient enough in the long-term to mean that the average individual cannot outperform the index. This is supported by Sharpe (1991), who argues that the average index must exceed active returns because the index comprises the return of all investors, including active investors. Both Sharpe and Samuelson (1974) suggest a passively tracked index fund as the most sensible investment in an informationally efficient market[2].

Arguing that stock price informational efficiency is not static, Lo (2004) compliments EMH by proposing the Adaptive Markets Hypothesis (AMH), which regards stock market informational efficiency as a dynamic measure over time. In AMH, informational efficiency shifts because the trade-off reward of arbitrage changes over time as investor rationality and

[2] Most investors are passive as found by Chetty et al. (2014), who discovered that 85% of Danish individuals did not adjust their pension allocation from 1995-2009 in response to any tax subsidy, regardless of size. Similarly, Crook (2024) found that compared to passive investing, active decisions can reduce annual return by 16%

the macroeconomic environment changes. This means that the alpha demanded by investors as compensation for arbitrage shifts as risk appetite changes. The adaptive investor rationality is most apparent during significant crises, when the market risk premium rapidly rises, meaning investors allocate less of their funds to risky assets. The dynamic nature of AMH supports Fama (1970) in that markets cannot be strong-form efficient at all times but are efficient enough for the weak-form of informational efficiency to hold in the long-term. Lo (2012) further explains that the competition for alpha means that opportunities for arbitrage asymptotically average zero in the long-term as alpha is limited to a number of managers who manage to beat the market in the short-term but fail to do so persistently. The consequence of AMH for active investing is crucial, as changing market conditions mean investors cannot use the same strategy to earn alpha across multiple time periods due to changes in the risk premium. Next to investor rationality, changes in technology over time has also made it more difficult for active investors to earn excess return, as found by Malkiel (2003).

Informational efficiency is also dynamic across regions, as the accuracy with which stock prices reflect their fair value varies. Borges (2010) and Lo (2012) found that newer stock markets in Europe and elsewhere are less efficient than older, more developed markets. Using multiple measures for efficiency, Baciu (2014) similarly found that across Europe, older stock markets were similarly more efficient. The paper also found that U.S. stock markets are significantly more efficient and liquid than those in Northern Europe, meaning prices in those markets update quicker to reflect reality as investors face smaller obstacles to engaging in arbitrage. Concentrating on one region, Kvedaras and Basdevant (2002) found that the Baltic stock markets were still inefficient compared to foreign markets after five full years of functioning capital markets, proving the effect of regionality. Based on these findings, it can be deduced that efficiency is not only dynamic over time in response to changing risk preferences but also in the structural differences between market regulations and the cost to trade on them. This is supported by Grossman and Stiglitz (1980), who found that some markets are inefficient because trading fees are too high to participate in arbitrage.

Cremers et al. (2016) further finds that strong-form EMH is heavily disputed in smaller markets due to higher search costs for finding mispricings and trading costs for arbitrage. In their view, this also explains the variance in active fund total expense ratios (TER) across regions, making the decision between funds more complicated and costly. In more efficient markets investors also face smaller TERs for active funds, meaning that the funds individuals have to choose between are more equal in their offerings (Wigglesworth, 2021). This is supported by Gârleanu and Pedersen (2022), who found that funds in inefficient markets have a higher TER because fund managers provide more value. Cremers et al. also found that active funds trade more and have a lower TER if there is greater competition from other active funds. They explain this by arguing that in competitive markets fund managers have to pass on more of their excess return to investors to gain an edge on their competitors, showing that fund fees are not exactly equal to the search costs incurred in finding mispricings. Developed markets are not, however, immune to price anomalies, as shifting investor rationality and changes in the macroeconomy still affect the relative level of informational efficiency in stock prices. A potential reason for the variance between regions is the amount of investors and fund managers, as found by Pastor and Stambaugh (2010), who discovered that mispricing of stocks is reduced when more managers chase alpha.

In recent years, analyses like Asness (2024) have claimed that market efficiency has decreased as passively managed index tracking funds grow in their share of stock markets. This follows the findings of Lipstein (2024), Gârleanu and Pedersen (2018) and Elhauge (2016), who find that growing passive ownership of companies, their indexing and the growing correlation between asset class returns are all factors that make markets inefficient. These factors have led to the creation of the inelastic market hypothesis by Gabaix and Koijen (2023), where stock prices do not rise in a one-to-one correlation with capital invested into them. This is in conflict with Pastor and Stambaugh (2010), who propose the idea that active investing faces decreasing returns to scale, meaning that fewer active investors leads to greater returns for the rest. This, in effect, means that markets decide the equilibrium share of capital in active equity funds. Asness has, however, argued that growing inefficiency does not lead to greater alpha for active investors because in inefficient markets it is costlier to hold positions in mispriced stocks when the crowd wisdom[3] disagrees.

### 1.2. Measuring Stock Market Efficiency

Having defined efficiency and deduced that it is an important factor in relation to active fund performance as fund managers in informationally efficient stock markets should not be able to generate persistent alpha, the next step is understanding how to measure it. For this purpose, this subchapter undertakes a survey of previous literature that has attempted to measure efficiency over time and across regions in order to discover the best fit for answering the research aim of this thesis.

[3] Referring to John Maynard Keynes, who said markets can stay irrational longer than investors can stay solvent

As discovered by Fama (1970), most researchers encounter the joint hypothesis test problem when attempting to evaluate EMH, meaning that any test of EMH also tests the validity of asset pricing models used. This means that it is near-impossible to confirm or refute the existence of EMH, instead most research focuses on using proxies to measure whether EMH holds in certain stock markets at certain points in time.

Using a systematic review of over 200 papers that specialise in market efficiency, Lim and Brooks (2011) found that most previous literature has focused on static research of whether stock markets are weak-form informationally efficient or not. An example of this is Fama and French (1992) and Sharpe (1991) who have used stock-returns to measure whether a stock market is efficient over a static sample period of returns. Silvasti et al. (2010) has fitted the model proposed by Fama and French to Nordic stock markets, finding that in these markets, statistically significant arbitrage opportunities exist.

An alternative method of measuring market efficiency is used by Kristoufek and Vosvrda (2012), who uses the autocorrelation between long-term returns and local herding of investor behaviour as a proxy for informational efficiency. Using this as a base for further research, Baciu (2014) finds that inefficient markets differ in the fact that past performance can be used to predict future returns. Similar to Bock and Geissel (2024), they both find that developed markets are more efficient.

In the systematic review of previous papers measuring market efficiency over time, Lim and Brooks (2011) further divides them into three subcategories: those that use a 1) non-overlapping period analysis, a 2) time-varying parameter model, and those using a 3) rolling estimation window. Papers following each of these three empirical models aim at focusing on a certain period of returns and analysing whether returns follow a *random walk* pattern, meaning does past performance predict future returns. One example of this is Urquhart and McGroarty (2016), who discovered using rolling estimation windows that from 1990-2014, return predictability varied greatly across markets and time. These papers studying time-varying efficiency are empirically similar to the models used by Lo (2012) in evaluating the adaptive markets hypothesis.

To measure the variance in stock market efficiency both over time and across regions, Tran and Leirvik (2019) has adopted the Adjusted Market Inefficiency Magnitude (AMIM). This measure grades the level of informational efficiency from -1 to 1 in order to facilitate easy comparison between markets over time. Like Ito and Noda (2015) and Noda (2016), AMIM uses an auto-regressive (AR) model to measure stock return autocorrelation over a time series. Ito and Noda measure the Time-varying Degree of Market Efficiency (TIME) across specific regions. As found in the model used by Urquhart and McGroarty (2016), TIME and AMIM both indicate that the information reflected in prices varies across time and regions. Building on AMIM, Bock and Geissel (2024) introduce a unique avenue of research by deriving a measure that quantifies the periods of inefficiency in a stock market. Using this measure on a dataset of all European stock index returns during 2007-2022, Bock and Geissel discover that developed markets have fewer periods of market inefficiency compared to emerging or frontier markets. Using the entropy of stock returns across time and regions, Patra and Hiremath (2022) has added support to AMH by discovering that certain economic factors such as regulation, domestic policy and politics affect investor rationality, which subsequently affect the informational efficiency of stock prices. They explain this by showing that transaction costs, poor governance, and smaller trading windows mean prices tend to reflect all available information less often. Concluding that market efficiency changes over time and across regions, there is a clear advantage in using a dynamic measure for measuring informational efficiency, which is the reason why this thesis also uses a dynamic index as a proxy for informational efficiency. A further overview of articles focusing on measuring market efficiency is visible in table 1.

**Table 1**
*Comprehensive overview of articles mentioned in chapter 1 for measuring efficiency.*

| Article | Period | Region | Methodology |
|---|---|---|---|
| Baciu, 2014 | 1999-2013 | Europe | Return memory and fractal dimension |
| Bock and Geissel, 2024 | 2007-2022 | Europe | AR of inefficiency moving averages |
| Ito and Noda, 2015 | $19^{th}$-$21^{st}$ c. | U.S. | Time-varying AR model |
| Kristoufek and Vosvrda, 2012 | 2000-2011 | World | Return memory and fractal dimension |
| Noda, 2016 | 1961-2015 | Japan | Time-varying AR model |
| Patra and Hiremath, 2022 | 1994-2017 | World | Entropy model of return randomness |
| Silvasti et al., 2010 | 1991-2019 | Nordics | Comparison of multi-factor portfolios |
| Tran and Leirvik, 2019 | 1962-2017 | U.S. | AR model of a time series of returns |
| Urquhart and McGroarty, 2016 | 1990-2014 | World | AR model of rolling window of returns |

Source: Compiled by the Author

### 1.3. Active Versus Passive Investing

Having defined market efficiency, its effect on alpha, and how to measure the relative level of efficiency in a stock market, it is important to understand why investors allocate assets into active funds and what factors play a role in fund manager performance. This subchapter examines the factors that affect the spread in returns between active and passive funds, aiming to connect previous arguments on efficiency and persistent fund manager skill into a framework that can predict the added benefit of active management.

Considering markets are in aggregate at least weak-form efficient, per Fama (1965, 1970), Lo (2004) and Jensen (1978), fund managers should not be able to persistently earn alpha. This line of thinking is confirmed by Malkiel (1995, 2003), Carhart (1997), and Bollen and Busse (2004), who find that the only predictably persistent factor in mutual fund returns is underperformance. This underperformance is consistent across fund structure and size[4], though Gerakos et al. (2021) has found that larger funds perform better.

Analysing fund manager skill, Hendricks et al. (1993) and Kosowski et al. (2007) have found that certain managers earn statistically significant alpha in different time periods but fail to persist in this outperformance over a long-term window of returns. Having deduced from Malkiel (1995) and Carhart (1997) that active fund alpha cannot persist after one-to-two years, it is necessary to understand what factors help predict this short-term alpha. Discussion of this topic in literature focuses on analysing whether successful stock picking is due to fund manager skill or luck.

Before analysing whether manager skill predicts active fund alpha, it is necessary to note that stock picking is difficult as the premium of the U.S. stock market over a portfolio of bonds since 1926 is composed of only four percent of all stocks per Bessembinder (2018). Further, many active managers may excuse high fund fees by promising skilful stock picking but actually end up subconsciously using common factor-investing models. In effect, this means that instead of actively picking stocks, they use a predefined factor that prints a list of undervalued stocks. This is supported by Carhart (1997), Fama and French (1992), Malkiel (2003), Øverseth and Andersen (2023), and Silvasti et al. (2010), all who support active alpha being predominantly down to factor-investing. After controlling for common factor-investing models, Øverseth and Andersen find that nearly all the alpha of Norwegian active funds from 1993-2023 is statistically insignificant, deducing that fund manager performance is down to luck or only investing in smaller stocks. Based on the research of Silvasti et al., Tyberg and Räftegård (2024) find that Nordic active fund managers only generate persistent alpha when managing funds aimed at the local market. This indicates that manager skill can be down to informational advantage, such as a local bias. Carhart specifically refutes Hendricks et al.

[4] Coggan, (2024), Livsey (2024), and Wigglesworth (2024) all find that under 20% of active funds outperform

(2003) in showing that even short-term persistent alpha can be explained by the use of common factor-investing models. Using simulations on active fund returns, Fama and French (2009) find that only a few active funds generate alpha that equals TER, and that individual fund manager skill is overshadowed by a majority of unskilled managers.

Carhart (1997) further explains that the persistent momentum in active fund alpha is down to some managers randomly deciding to hold some of the best-performing stocks from last year, which then keep performing, making it look like they follow a momentum strategy. Even this edge, however, disappears after a year as active fund alpha is no longer statistically significant after a one-year window in his review of mutual fund returns from 1962-1987. In this manner, Carhart introduces the measure of luck in active fund manager performance, which may explain a large part of the statistically significant short-term alpha of active funds. This is supported by some active fund managers themselves claiming that in multiple occurrences, unforeseen circumstances that they did not expect contributed to their excess return (Barrett, 2024). The effect of luck on active fund alpha is further explained by the *skill paradox* of Maubossin (2012), stating that in a market with many equally skilled managers, luck is more important as the skills of the fund managers offset each other. An overview of articles researching fund manager skill and active fund alpha is in table 2.

**Table 2**

*Comprehensive overview of articles used in chapter 1 that research active equity fund alpha.*

| Article | Research avenue | Region | Results |
|---|---|---|---|
| Bollen and Busse, 2004 | Alpha persistence | U.S. | Alpha is only short-term |
| Carhart, 1997 | Alpha persistence | U.S. | Factor-investing explains alpha |
| Fama and French, 1992 | Stock returns | U.S. | Common factors explain alpha |
| Fama and French, 2009 | Alpha composition | U.S. | Alpha is a statistical outlier |
| Hendricks et al., 1993 | Alpha prediction | U.S. | Past returns predict future alpha |
| Kosowski et al., 2007 | Alpha prediction | U.S. | Luck does not explain all alpha |
| Malkiel, 1995 | Alpha persistence | U.S. | Does not support manager skill |
| Øverseth and Andersen, 2023 | Alpha prediction | NOR | Alpha is down to luck or factors |
| Pastor and Staumbaugh, 2010 | Active fund size | U.S. | Find decreasing returns to scale |
| Tyberg and Räftegård, 2024 | Alpha during crises | Nordic | Only local funds generate alpha |

Source: Compiled by the Author

Considering that EMH states that an at least weak-form efficient market should not allow for persistent alpha by any active investor and research that shows active fund alpha is down to luck or factor-investing, it is apparent that active fund AUM is puzzling. Even as passively managed funds have grown significantly, active funds still have large AUMs, which, according to Wigglesworth (2021), is hard to explain if investors are rational. Pastor and Stambaugh (2010) explain this discrepancy by stating that active investing faces decreasing returns to scale, meaning the less money that is allocated to active funds, the greater is the average return of the remaining active funds, with the rest in passive funds. They further deduce that individuals have to invest in active funds and encounter negative alpha in order to correctly adjust their allocation into passive funds. This is further supported by Cremers et al. (2019), who find that since 1997, the smaller share of capital allocated to active funds has made it a better choice for rational investors. The large AUM of active funds has also been attributed to irrational investors. Gruber (1996) and Vokata (2021) have found that some investors fall prey to predatory marketing schemes of complex active funds that display large returns out of context, using the fact that the average rational investor cannot price in fund manager skill. This practice has been referred to as volatility laundering by Wigglesworth, as it preys on the irrational wish of investors to believe their skill in fund selection is what decides their long-term returns and not exogenous factors. Gârleanu and Pedersen (2018, 2022) and Pedersen (2018) argue that the decision between active and passive funds depends on investment size and the number of funds available as the cost to discover informed fund managers decreases according to economies of scale.

Pedersen (2018)[5] discovered that active funds perform better in inefficient markets, supporting the belief that efficiency moderates active fund alpha and that in these markets active funds have higher fees and are more risk averse. According to Pedersen and research by AQR Capital Management (2018), this is because in inefficient markets, only large funds have enough capital to act on arbitrage opportunities because of high information costs and transaction fees. These findings are confirmed by Ravenscroft (2024), who finds that from 1999-2023, 75% of active managers outperform their benchmark in emerging markets but only 38% manage to do so in the U.S. due to the informational advantage in U.S. prices. According to Ravenscroft and Pedersen, this is down to the fact that large U.S. companies have more analysts and computer algorithms covering them and trading in their prices daily. As found by Pedersen, this means that investors in illiquid markets invest more capital in actively managed funds as active fund alpha is higher in these markets.

[5] Further arguing *passive* investing does not exist because index tracking funds also have to buy and sell stocks

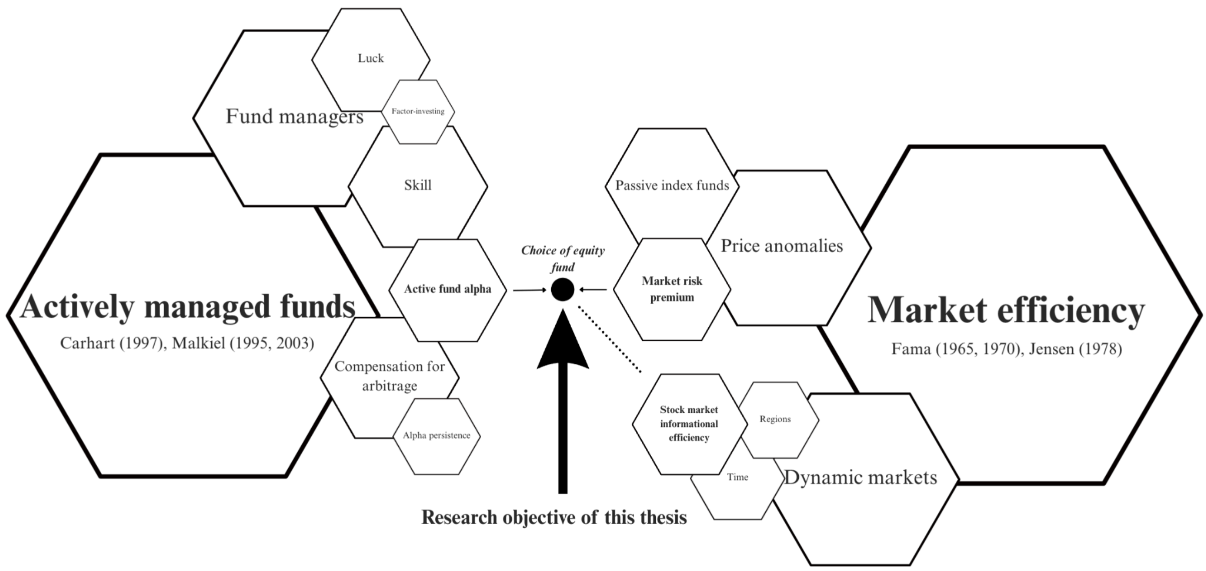


*Figure 1.* Visualisation of the aim of this thesis to fill the research gap. Model (ii) attempts to fulfil this by answering whether market efficiency is a moderator (dotted line) of the relationship between active fund alpha and the market risk premium.
Source: Compiled by the Author

Having concluded that informational efficiency affects stock market returns and that it is best measured with a dynamic parameter, this subsection shows that prior research indicates that while active fund alpha is largely down to luck and is short-term, informational efficiency still plays an unidentified role in the decision of funds. As such, it is necessary to fill this gap (figure 1) by understanding whether stock market efficiency predicts active fund alpha. For this purpose, chapter two introduces a critical analysis of the empirical models and dataset used in fulfilling the research aim.

# 2. Data and method

This chapter offers a critical view of the empirical methodology chosen for this thesis and describes the data used. It is divided into two subsections that describe data collection and the reasoning behind the chosen methodology.

## 2.1. Data

In order to fit an empirical model to attempt to answer the research aim, a dataset of active and passive fund returns, their identifying features, and the variables capturing market performance is necessary. The period to be analysed was chosen as 2011-2024 as this excludes the global financial crisis, while providing a large sample of returns but being recent enough to assure that returns data is accessible for most funds. The regions chosen are a diverse selection of five large, advanced economies that form the majority of the MSCI World index and a subset of smaller, European, markets.

For 82 funds[6], their quarterly returns, TER and management style were collected. For finding funds, fund screeners were used to detect funds that fit the regional stock categories. After gathering a list of fitting funds, they were filtered by management style and sorted by AUM. The biggest funds with more than five years of persistent data for returns were chosen. Fund returns and TERs were gathered from the fund broker information dashboards. In order to prevent dividend return from distorting results, focus was placed on accumulating funds.

For regions[7], their quarterly market index returns, risk-free rate, Fama-French factors, and efficiency score was collected. For the risk-free rate, the quarterly yield of each region's 10-year treasury bond from OECD (2025) is used. This approach follows Øverseth and Andersen (2023), who used CAPM and Fama-French factors to model mutual fund performance compared to the base benchmark return. For the funds representing the Baltics region, Lithuania's 10-year yield is used as the risk-free rate as the funds are domiciled in the given country. Each region's main MSCI (2025) index is used as the market return, except for the Baltics, which uses the return of the local Baltic Benchmark Index.

For measuring fund return sensitivity to common factor-investing models, the Fama and French (2025) Small-minus-Big and High-minus-Low factors for each region were used. The formulas for calculating these are below on equations (1) and (2).

(1) $$SMB = \frac{1}{3} \cdot (SV + SN + SG) - \frac{1}{3} \cdot (BV + BN + BG)$$

Where $SMB$ - the return for a portfolio holding the bottom 30th percentile of stocks

$S/B \cdot V$ - The bottom 10% and top 90% market cap-weighted value stocks

$S/B \cdot N$ - The bottom 10% and top 90% market cap-weighted neutral stocks

$S/B \cdot G$ - The bottom 10% and top 90% market cap-weighted growth stocks

(2) $$HML = \frac{1}{2} \cdot (SV + BV) - \frac{1}{2} \cdot (SG + BG)$$

Where $HML$ - the return for a portfolio holding the highest book-to-market ratio stocks

$S/B \cdot V$ - The bottom 10% and top 90% market cap-weighted value stocks

$S/B \cdot G$ - The bottom 10% and top 90% market cap-weighted growth stocks

[6] Comprehensive overview of equity funds included in Appendix A
[7] List of regions included in Appendix B

Due to the aforementioned benefits of measuring market efficiency over time, this thesis uses a dynamic index of market efficiency. Thus, as a proxy for market efficiency, the IMF-World Bank (WB) index for Financial Market Efficiency is used, which captures the local stock market turnover ratio from 0 to 1. It does this by calculating the ratio of annually traded stocks to the total annual stock market capitalization (Svirydzenka, 2016). Since the index omits data for the Baltic region, the same formula is used to impute values using Nasdaq Baltic (2025) data. The IMF-WB index provides data up to 2021 in the dataset, which means that imputed data from the last year is used as a proxy for the remaining years. To determine whether this affects the results, the main models were also run only on data from 2011-2021, with results visible in Appendix C. The sensitivity analysis showed that limiting the data by three years reduces the explanatory power of the model, as such, it is decided for the model to also cover 2022-2024.

The IMF-WB index is a part of the wider Financial Markets index, which also captures companies' access to financial markets, the ratio of stocks traded to GDP and the total number of bond issuers (Svirydzenka, 2016). In order to control for potential omitted variable bias by only using the subindex, the main models were also run on the complete Financial Markets Index. Since the complete index explains less of the variance in active fund alpha, the subindex is used. The efficiency scores for European markets from Bock and Geissel (2024) were also used to test the model's sensitivity to using different proxies, but this indicator similarly explained less of the variance in net returns, as visible in appendix D.

### 2.2. Methodology

In order to fulfil the research aim, two empirical models are introduced that (i) identify the factors that affect the composition of fund alpha, and (ii) explain the sensitivity of active fund alpha to stock market efficiency. To achieve this task, the methodology of model (i) follows accepted CAPM models to explain active fund alpha. The analysis follows a linear panel data two-way fixed effects regression that accounts for market risk premium, volatility, original Fama-French (1992) factors, and efficiency. Building on Jensen's (1967) alpha and the model used by Sharpe (1991), a pricing model that estimates the alpha of all equity funds is used that aims at explaining the factors that play a role in predicting fund returns.

The equation for model (i) is:

$$R_E = \alpha + \beta_1 \cdot (R_m - r_f) + \beta_2 \cdot SMB + \beta_3 \cdot HML + \beta_4 \cdot X_{1it} + \beta_5 \cdot X_{2it} + \varepsilon_{it} \tag{3}$$

Where $R_E$ - estimated equity fund net return

α - estimated excess return

$\beta_1$ - sensitivity to the market risk premium

$R_m$ - market return

$r_f$ - the risk-free rate

$\beta_2$ - sensitivity to the SMB factor

$SMB$ - Fama-French Small–minus-Big portfolio returns

$\beta_3$ - sensitivity to the HML factor

$HML$ - Fama-French High-minus-Low portfolio returns

$\beta_4$ - sensitivity to market efficiency

$X_1$ - stock market informational efficiency

$\beta_5$ - sensitivity to market volatility

$X_2$ - market volatility

ε - the residual error variable capturing all unmeasured and omitted variables

Having confirmed whether informational efficiency affects net returns in model (i), it is necessary to investigate whether it can be used to predict active fund α. For this purpose, model (ii) includes an interaction term between market efficiency and the market risk premium to investigate whether inefficiency predicts when active funds generate alpha. The null hypothesis for model (ii) states that at a 0.05 significance level, efficiency is not a statistically significant predictor of the relationship between active fund alpha and the market risk premium. The alternative hypothesis means that if relative efficiency is known, then the investor deciding between funds can estimate whether an active fund will generate a return in excess of their compensation for sitting in a passive index fund, the market risk premia.

The equation for model (ii) is:

(4) $$Y = \beta_1 \cdot X_{1it} + \beta_2 \cdot X_{2it} + \beta_3 \cdot \beta_2 \cdot (X_{1it} \cdot X_{2it}) + \beta_4 \cdot X_{3it} + \varepsilon_{it}$$

Where Y - active fund alpha

$\beta_1$- sensitivity to market efficiency

$X_1$- stock market informational efficiency

$\beta_2$- sensitivity to the market risk premium

$X_2$- the market risk premium

$\beta_3$- the interaction term between market efficiency and the market risk premium

$\beta_4$ - sensitivity to market volatility

$X_3$ - market volatility

$\varepsilon$ - the residual error variable capturing all unmeasured and omitted variables

Before deciding whether to use an ordinary least squares (OLS), fixed effects (FE), or a random effects (RE) model, the dataset needs to fit the least squares assumptions for unbiased coefficients. The methodology in this chapter for the least squares assumptions follows Stock and Watson (2003). The first of these assumptions, $E = (\varepsilon | X = x) = 0$, is fulfilled as the OLS model controls for the error term variance over time through an intercept. The second assumption, that the variables in the model are identically and independently distributed, is fulfilled because the sampling across regions is random. The third, and last, assumption that extreme outliers are rare is also fulfilled as the analysis for outliers indicated no unexpected outliers. Thus, assuming the assumptions hold, the estimated OLS coefficients are approximately distributed and are approximate estimates. The OLS regression estimated coefficients are, however, liable to the omitted variable bias in cases where an omitted variable is a direct determinant of the dependent variable and is correlated with the included independent variable.

Because of this, and to capture more of the variance within fund alpha, the dataset is transformed into a balanced panel dataset so that dynamic individual heterogeneity within returns is accounted for. The panel data is used for two-way FE regressions, wherein the error term accounts for dynamic within-group variance. The RE model is not relevant for use in this model since it prevents analysing within-group variance, which is important for answering whether changes in efficiency within regions affects fund performance. Furthermore, the Hausman test and F test for individual effects were run on the FE and RE models, which confirmed that a FE model was more fitting. The results of the OLS and RE regressions in model (ii) are visible in Appendix F.

In terms of limitations, the thesis omits two significant variables that may affect the historical net returns of active funds, changes in TER and survivorship bias, where managers close badly performing funds, leaving only successful funds in the eventual available dataset of funds. It can also be assumed that the model lacks a number of region-specific variables that can further help explain active fund alpha. This can further be seen from the $R^2$ of model (ii), which shows that, while the variables included are statistically significant, they do not explain much of the variance in alpha. This omitted variable bias is, however, reduced since the model uses both time and entity fixed effects, meaning it accounts for missing time-varying variance for funds and regions. A number of other measures also exist that can be used as proxies in order to measure market efficiency than the three used in this thesis.

# 3. Results and discussion

This chapter describes the results of the descriptive statistics analysis that was run in the statistical software, R, on the variables included in the dataset, the results of the empirical models, and discusses these results in the context of the research aim of this thesis.

First, a dispersion analysis of net fund returns by management style was performed, seen in figure 2, which indicates that fund returns are similar across management styles, with passive funds having a slightly larger average return. Figure 2 also indicates that passive funds have larger outliers, showing that active funds can protect against extreme deviations. This dispersion in returns by region is visible in figure 3.

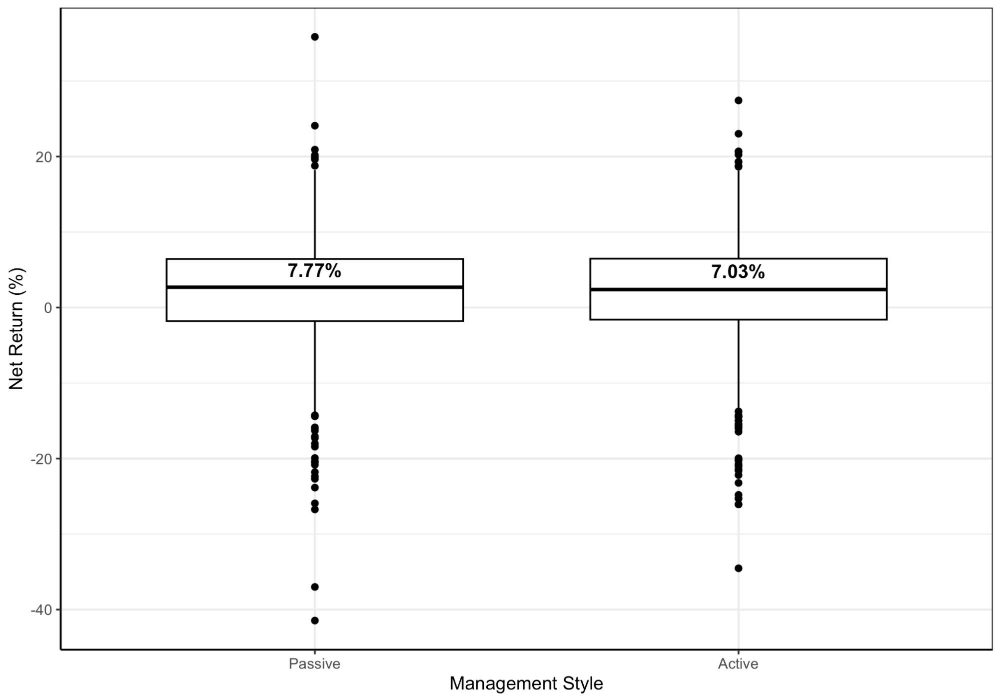


*Figure 2.* Boxplot of annualised fund net return during 2011- 2024. Dots indicate extreme returns outside the IQR (25%-75% of observations). Line and text are the median and mean. Source: Compiled by the Author

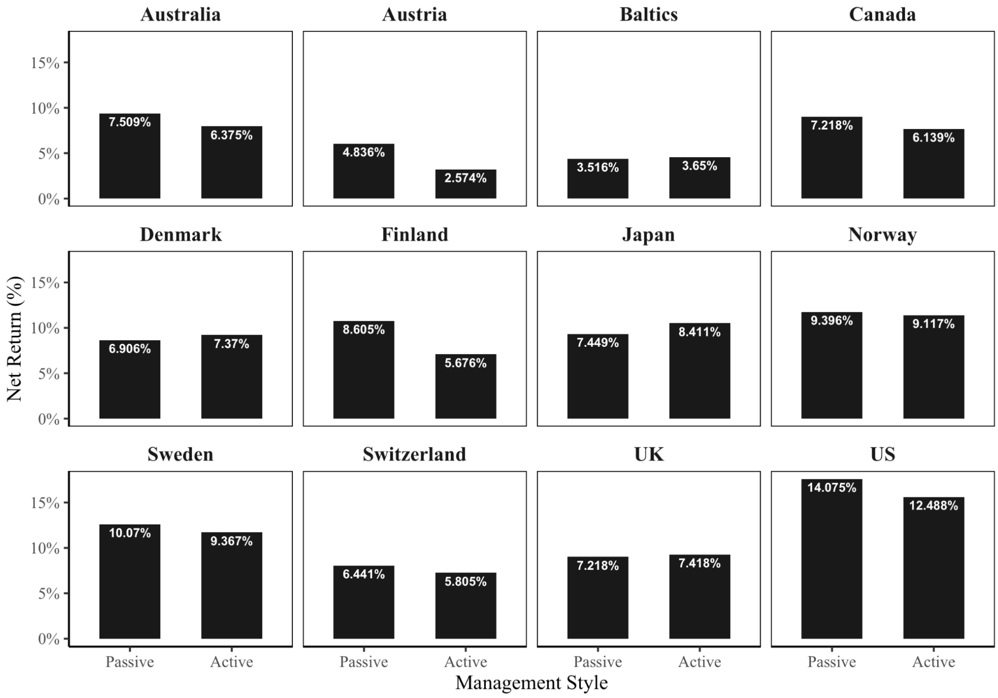


*Figure 3.* Annualised fund net return from 2011-2024 by region. Number is the mean return.
Source: Compiled by the Author

In order to discover outliers, each numerical variable in the dataset was run through box-whisker graphing plots. No special outliers were detected except common extreme fund returns during macroeconomic crises, primarily during 2011 and 2020.

To further understand the distribution of each variable, a descriptive statistics table was created. The summary table of descriptive statistics for model (i) and (ii) are visible below in table 3 and 4 respectively. Initial analysis indicates that passive fund return is more volatile and outperforms active funds on average by 0.037% each quarter, 0.313% after fees.

**Table 3**
*Descriptive statistics table of the dataset for model (i).*

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Median | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|---|
| Fund Return | 4,400 | 2.279 | 7.992 | -41.330 | -1.340 | 3.040 | 7.102 | 35.980 |
| Total Expense Ratio | 4,400 | 0.233 | 0.173 | 0.000 | 0.070 | 0.212 | 0.400 | 0.552 |
| Efficiency Index | 4,400 | 0.757 | 0.233 | 0.040 | 0.560 | 0.810 | 1.000 | 1.000 |
| Market Return | 4,400 | 1.668 | 8.954 | -46.680 | -2.450 | 2.570 | 7.170 | 37.430 |
| Risk-free Rate | 4,400 | 0.384 | 0.310 | -0.200 | 0.120 | 0.385 | 0.600 | 1.310 |
| Market volatility | 4,400 | 7.762 | 4.930 | 1.060 | 3.760 | 6.300 | 13.360 | 31.480 |
| Small-minus-Big | 4,400 | -0.247 | 3.571 | -10.800 | -2.600 | 0.000 | 2.000 | 20.650 |
| High-minus-Low | 4,400 | 0.080 | 4.927 | -18.360 | -2.500 | 0.000 | 3.000 | 17.180 |
| Net Fund Return | 4,400 | 2.046 | 7.997 | -41.455 | -1.566 | 2.810 | 6.900 | 35.855 |
| Market Risk Premium | 4,400 | 1.284 | 8.969 | -46.660 | -2.712 | 2.140 | 6.840 | 37.490 |

Notes: Net Fund Return and Market Risk Premium computed using pre-existing variables.
Source: Compiled by the Author

**Table 4**
*Descriptive statistics table of the dataset for model (ii).*

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Median | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|---|
| Passive Fund Net Return | 672 | 1.943 | 7.853 | -41.455 | -1.799 | 2.694 | 6.432 | 35.855 |
| Active Fund Net Return | 672 | 1.758 | 7.755 | -34.531 | -1.592 | 2.386 | 6.475 | 27.429 |
| Active fund alpha | 672 | -0.184 | 2.566 | -10.613 | -1.355 | -0.157 | 1.091 | 12.990 |
| Market Risk Premium | 672 | 1.217 | 8.871 | -46.660 | -2.615 | 1.895 | 6.455 | 37.490 |
| Market volatility | 672 | 7.386 | 4.845 | 1.060 | 3.690 | 5.790 | 10.220 | 31.480 |
| Small-minus-Big | 672 | -0.244 | 3.559 | -10.800 | -2.555 | 0.000 | 2.000 | 20.650 |
| High-minus-Low | 672 | 0.072 | 4.897 | -18.360 | -2.640 | 0.000 | 3.000 | 17.180 |
| Efficiency Index | 672 | 0.699 | 0.285 | 0.040 | 0.558 | 0.810 | 1.000 | 1.000 |

Notes: Management Return Spread computed by subtracting the two net returns.
Source: Compiled by the Author

The dynamic spread in returns between active and passive funds is visible below in figure 4, where it can be seen that active funds outperformed their passive counterparts for only four out of the fourteen years in the model. It is visible that the greatest active fund underperformance is during market stress, indicating a relationship with market risk premia.

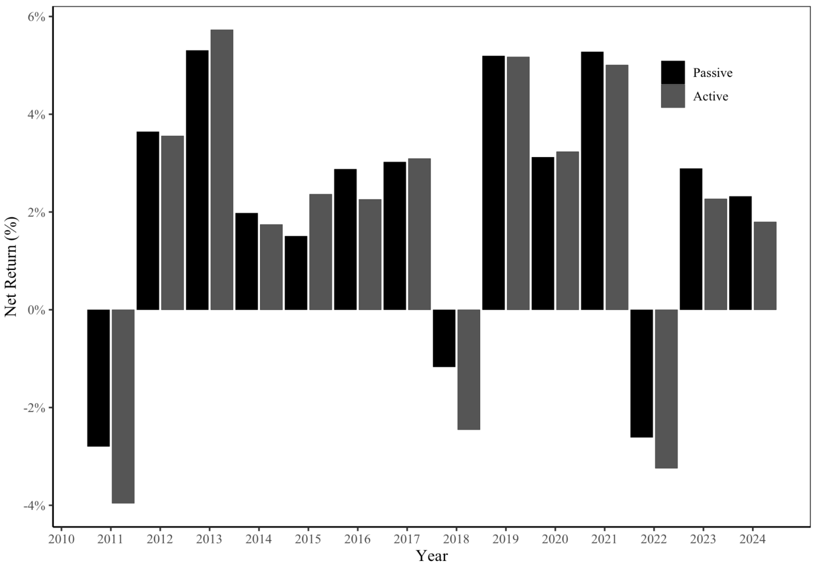


*Figure 4.* Annual net return by management style during 2011-2024.
Source: Compiled by the Author

After testing for outliers, the numerical variables in the dataset were controlled for between-variable correlation with a Pearson pairwise correlation matrix, the results of which are visible in Appendix G. The matrix indicates a strong positive relationship between fund returns and the market return, which is to be expected as the market return consists of stocks that funds invest in. There is also a weak negative relationship between efficiency and TER, indicating that funds in less efficient countries possess higher fees, as stipulated by Patra and Hiremath (2022).

Following the initial data analysis, the distribution of fund returns was analysed using an autocorrelation function (ACF) for lagged observations, the result of which is in figure 5. This shows the strong effect of lags on predictable return observation, meaning that at least in the short-term, stock prices are inefficient, since they have a predictive memory function meaning that past returns can be used to predict future performance. This is indicated by the fact that lags from the first 8 quarters (two years) are the most significant, thus, supporting previous research in that short-term anomalies are arbitraged away in the long-term and active fund alpha is not persistent after one-to-two years.

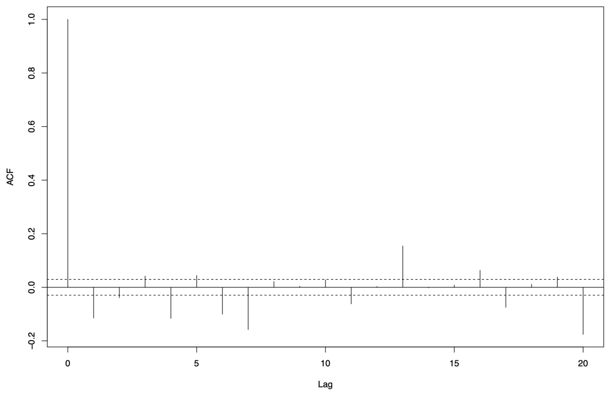


*Figure 5.* Autocorrelation variance in quarterly returns.
Source: Compiled by the Author

Following this finding, a stationarity test was run on fund returns using the Dickey-Fuller (AR) test, the results of which (H0: data is not stationary; p-value < 0.01) support assuming that fund returns are stationary. This supports at least definite weak-form efficiency as the memory function does not have a long-term predictability effect. In conjunction, these two results can be used to presume that stock prices in the dataset are inefficient in the short term up to 2 years, but in the long-term follow a *random walk* and are weak-form efficient, supporting Fama (1970) and Lo (2004).

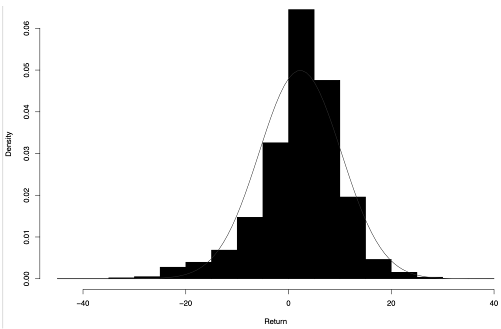


*Figure 6.* Histogram distribution of observations of fund returns.
Source: Compiled by the Author

Next, the fund returns were tested for normality, returns were found not to follow a perfect bell-curve, visible in figure 6, and had skewness and kurtosis scores (-0.765 and 4.95 respectively) indicating extreme fat tails and slight negative skewness. Active fund alpha also had extreme fat tails and large kurtosis but was not skewed (6.90 and 0.01 respectively).

Following the initial data analysis steps, the dataset was manipulated to fit the distribution for model (ii). This consists of calculating the excess return of active funds over passive funds, the active fund alpha, the distribution of which is visible by region in figure 7. The minimum and maximum alpha in one quarter during the observed 14-year period was -10.61% and +12.99% respectively. A further analysis using net returns indicated a Sharpe ratio of 0.442 for passive funds and 0.382 for active funds.

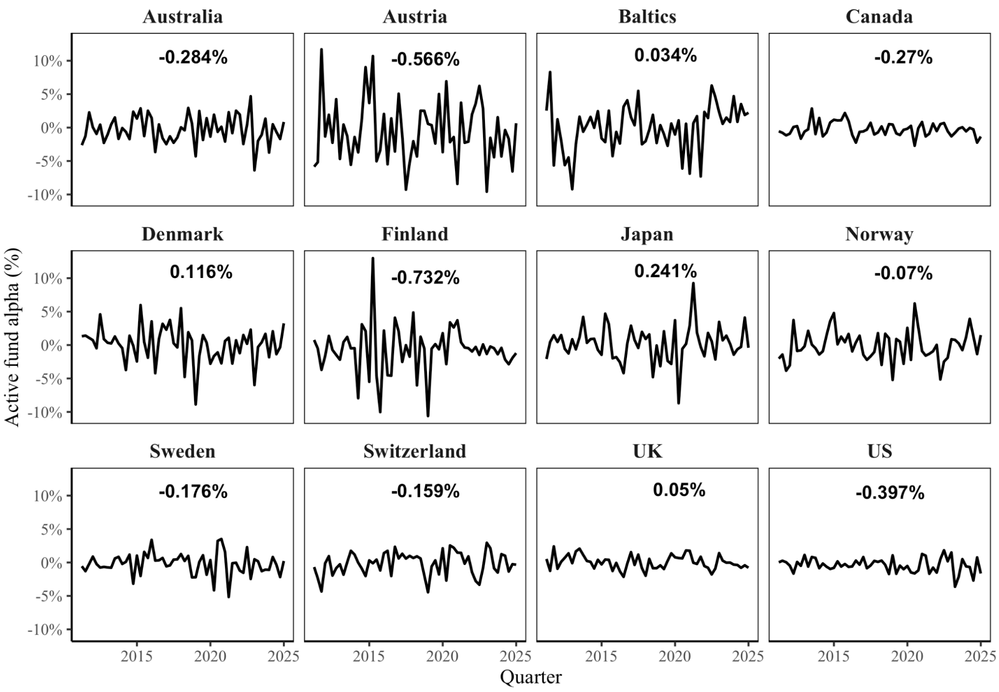


*Figure 7.* Average quarterly active fund alpha by region in 2011-2024. Number is the mean. Source: Compiled by the Author

In order to evaluate possible heteroskedasticity, the Breusch-Pagan test was run on both models, indicating that the standard errors are not homoscedastic as the alternative hypothesis (H0: data is homoscedastic, p-value < 0.05) could not be rejected. As such, all the models in this thesis use robust standard errors. A variance inflation factor (VIF) test was also run on models (i) and (ii) to test for multicollinearity, the results of which showed no reason to suspect multicollinearity as the test results were below the VIF minimum bound (5).

**Table 6**
*Results of model (i)*

| | Net quarterly return |
|---|---|
| Stock market efficiency | -2.345*** |
| | (0.554) |
| Market risk premium | 0.495*** |
| | (0.023) |
| Market volatility | -0.054*** |
| | (0.014) |
| Small-minus-Big | -0.033 |
| | (0.030) |
| High-minus-Low | -0.061 |
| | (0.039) |
| Individual fixed effects | Yes |
| Time fixed effects | Yes |
| *N* | 4,400 |
| $R^2$ | 0.326 |
| Adjusted $R^2$ | 0.303 |
| *Notes:* | ***Significant at the 1 percent level. |
| | **Significant at the 5 percent level. |
| | *Significant at the 10 percent level. |

Source: Compiled by the Author

As seen in table 6, a thorough analysis of model (i) illustrates that, using a two-way FE regression, informational efficiency, market risk premium, and volatility are statistically significant predictors of fund returns at a five percent level. The variables included in the model explain 32.6% of the variance in fund net returns. The coefficient for stock market efficiency shows that an increase in stock price informational efficiency by 1, all else held constant, decreases the quarterly net return of all funds by 2.345 percentage points. The market risk premium coefficient shows that an increase in the market risk premium by one percentage point leads, all else held constant, to a 0.495 percentage point increase in returns. The volatility coefficient shows that an increase in the market standard deviation by one percentage point leads, all else held constant, to a 0.054 percentage point decrease in returns. The Fama-French SMB and HML factors were not statistically significant predictors of fund returns in the context of the complete dataset including all regions.

These resulting coefficients indicate that local market return and volatility are statistically significant predictors of returns, which is to be expected, as the funds invest in the same universe of equities. The model also showed that the Fama-French factors, however, are not statistically significant predictors of fund returns when using a two-way FE regression, the reason for this may be that the factors are continent-specific and not regional. The statistical insignificance of these coefficients also lends support to AMH, which states that markets are dynamic over time and mispricing anomalies are arbitraged away, meaning factors that provided statistically significant alpha in the past cannot predict future returns. The consequence of this for fund managers is that they have to adapt their methodology for stock picking as macroeconomic conditions and investor rationality changes, making it more likely that fund manager alpha in any certain period is luck-based, supporting Fama (2009).

An analysis of model (i) was also run on all regions in the dataset, the results of which can be seen in Appendix H. Focusing on Norway, the results indicate that returns follow a similar pattern as in the complete dataset. For Norway, however, the Fama-French HML factor is a statistically significant predictor of fund returns, lending support to the findings of Øverseth and Andersen (2023) and Silvasti et al. (2010), who discovered that in Norway and the rest of the Nordics, alpha can largely be attributed to the use of Fama-French factors.

**Table 7**
*Results of model (ii)*

| | Active fund alpha |
|---|---|
| Stock market efficiency | -0.802 |
| | (0.956) |
| Market risk premium | $-0.248^{***}$ |
| | (0.059) |
| Market volatility | $0.041^{**}$ |
| | (0.020) |
| Market risk premium (Efficiency = 1) | $0.216^{***}$ |
| | (0.076) |
| Individual fixed effects | Yes |
| Time fixed effects | Yes |
| *N* | 672 |
| $R^2$ | 0.111 |
| Adjusted $R^2$ | 0.008 |
| *Notes:* | $^{***}$Significant at the 1 percent level. |
| | $^{**}$Significant at the 5 percent level. |
| | $^{*}$Significant at the 10 percent level. |

Source: Compiled by the Author

As seen in table 7, the results of model (ii) indicate that, while market efficiency is not an independent statistically significant predictor of active fund alpha, it moderates the relationship between the market risk premium and active fund alpha. The market risk premium and market volatility are also statistically significant estimators at a five percent significance level. The variables included in the model explain 11.1% of the variance in active fund alpha. The Market Risk Premium coefficient shows that an increase in the risk premium by one percentage point leads, all else held constant, to a 0.248 percentage point decrease in active fund alpha. The volatility coefficient shows that an increase in the market standard deviation by one percentage point leads, all else held constant, to a 0.041 percentage point increase in active fund alpha. The interaction term coefficient shows that a 100% increase in market efficiency reduces, all else held constant, the strength of the relationship between the market risk premium and management spread by 0.216 percentage points. This finding indicates that the relationship between market risk premium and active fund alpha is nearly negligent in completely efficient markets. The relationship is further visible in the visual illustration in figure 8, which portrays that in more efficient markets (+ 1 Std. Dev.), dynamic movement in the market risk premium has a smaller effect on active fund alpha.

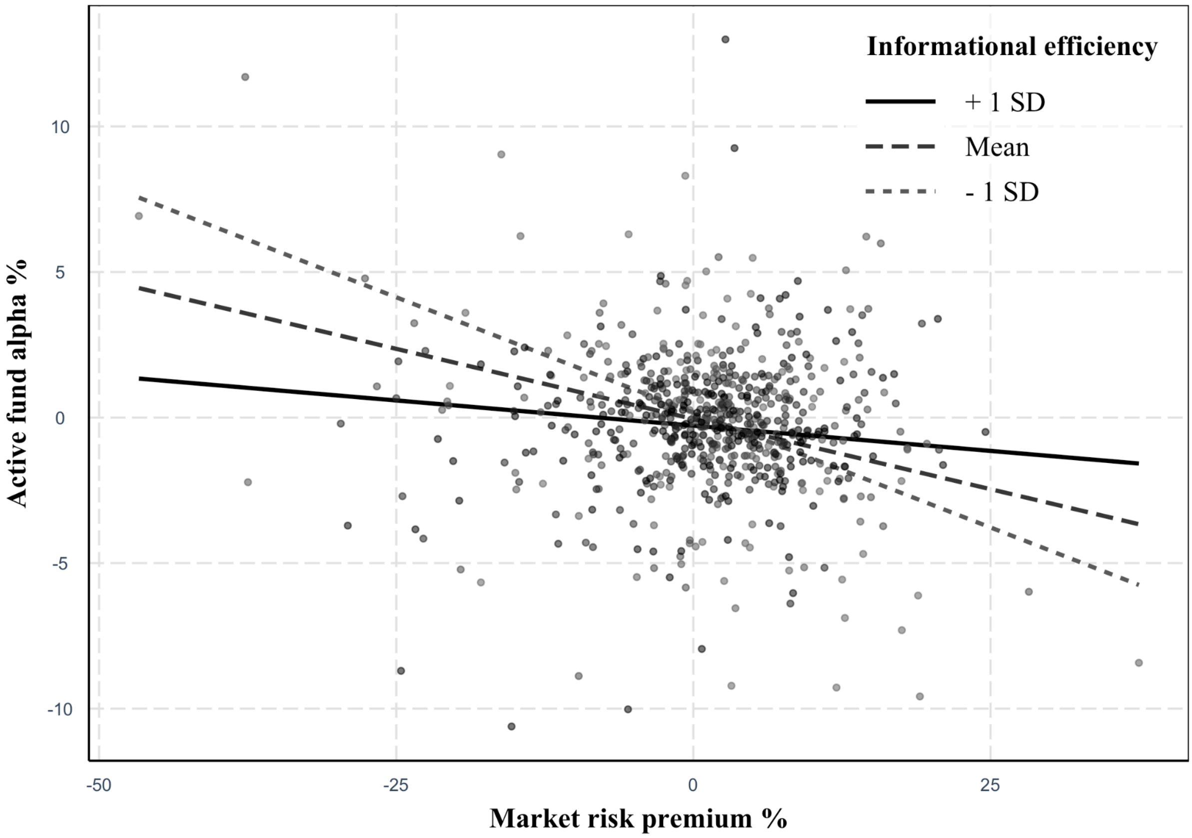


*Figure 8.* The interaction of market efficiency as a moderator in the relationship between active fund alpha and market risk premium
Source: Compiled by the Author

The descriptive statistics analysis indicated that active funds underperform their passive counterparts even before fees are subtracted, supporting the findings of Fama (2009) in that the average active fund cannot, in the long-term, earn market-beating alpha. The autocorrelation and stationarity analyses illustrate that, while stock prices can be inefficient in the short-term and have anomalies, these are quickly arbitraged, meaning prices are efficient in the long-term. In summary, while there are cases of statistically significant active fund alpha, this does not persist past the short-term and is overshadowed by the majority of managers underperforming net of fees, as found by Fama. A further OLS and RE regression were run on TER and fund returns, finding that in no region is TER a statistically significant predictor of returns, disproving that the high fees of active funds is compensation for search costs. These findings, combined, lend support to the idea of informationally efficient stock prices affecting opportunities for stock picking arbitrage.

Model (ii) strengthened the findings of the first model in that the market risk premium and volatility are statistically significant predictors of not only active and passive fund returns but the spread between them. Further, the statistically significant coefficient of the interaction term indicates that the spread between active and passive funds is less sensitive to the equity risk premium in more efficient regions. This relationship, portrayed visually in figure 8, supports EMH in that in an efficient market, individuals should have no inherent advantage with which they can earn a return above that of the market average. Following Asness (2024), it can be assumed that due to technological and regulatory advancements in efficient markets, prices react quicker to news, regardless of whether the market risk premium is high or low. This lends support to the idea that market efficiency has an effect on how managers generate alpha and supports previous research such as Patra and Hiremath (2022) in finding that inefficient markets provide more opportunities for stock picking. The finding that market efficiency mediates the market risk premium also follows Pedersen (2018), who found that less efficient markets are also more risk averse, leading to a greater risk premia for equities.

As a whole, the empirical model results indicated that, while market efficiency does not directly predict the alpha of actively managed funds, it is a statistically significant moderator of how active fund alpha responds to the market risk premium. This finding supports the theory that stock price informational efficiency affects successful stock picking, supporting Fama (1965, 1970), Jensen (1978), and Malkiel (2003). In economic terms, this means that individual investors have to include market efficiency in their utility function when predicting whether an active or passive fund will perform best in their investing window. When the market premium shifts, this may mean that investors in active funds have to perform more transactions into passive funds, depending on the efficiency of their region. For fund manager skill, managers in inefficient markets have less skill in outperforming when the equity risk is higher, disproving previous research that has found merit in active investing during times of crisis.

## 4. Conclusion

This thesis answers the question whether stock market informational efficiency predicts actively managed equity fund alpha by applying two empirical models to a dataset of equity fund returns from 2011 to 2024. In doing so, the aim is to fulfil an identified gap in previous academic journals connecting the relative efficiency of stock prices and the decision by individual investors whether to allocate capital into actively or passively managed funds.

The results indicate that the informational efficiency of stock prices, meaning how much of available information they convey, is a statistically significant predictor of the net return of all equity funds and a moderator of the relationship between active fund alpha and the market risk premium. The economic context of these findings means that in inefficient markets, active fund manager alpha in stock picking is greatly negatively affected by a rise in the risk premium of equities during times of crisis. This confirms previous findings by Fama (2009) and Carhart (1997) in deducing that market efficiency affects the distribution of stock price anomalies available for skilled active fund managers to arbitrage. As theorised, the findings connect the avenues of research discussing market efficiency and the decision between fund management style in developing the existing toolset for individual investors. Considering that investing into a passive index tracking fund nets the investor the market risk premium, it is wise, when choosing between funds, to investigate the local efficiency to understand the potential for active fund managers to outperform.

For future research, it is possible to analyse whether the inclusion of only ETFs can affect the results, as they tend to be more equally priced compared to their passive counterparts. Similarly, more proxies for market efficiency can be included, such as the average bid-ask spread in the market, the market opening hours and the trade settlement time. The data for fund returns can also be widened back to 2000 to show how greater changes in market efficiency affects active fund alpha; this, however, requires access to historical total expense ratios, allowing for measuring the dynamic nature of active fund fee structures.

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## Appendices

### Appendix A: List of funds included in the dataset

| Domicile | ISIN | Management | Period |
|---|---|---|---|
| Finland | FI4000010533 | Passive | 2011-2024 |
| Finland | FI0008800016 | Active | 2011-2024 |
| Finland | FI0008803119 | Active | 2011-2024 |
| Norway | FI4000566112 | Passive | 2011-2024 |
| Norway | FI4000391099 | Active | 2019-2024 |
| Sweden | SE0002591016 | Passive | 2011-2024 |
| Sweden | FI4000088000 | Active | 2014-2024 |
| Sweden | SE0000625238 | Active | 2011-2024 |
| Sweden | SE0003653302 | Active | 2011-2024 |
| Denmark | DK0010252873 | Active | 2011-2024 |
| Denmark | DK0010266238 | Passive | 2011-2024 |
| Norway | NO0010582976 | Passive | 2011-2024 |
| Norway | NO0010819915 | Active | 2011-2024 |
| Sweden | SE0007074075 | Passive | 2011-2024 |
| Sweden | SE0000996233 | Active | 2011-2024 |
| Sweden | LU1679011665 | Active | 2019-2024 |
| Sweden | LU1349502002 | Passive | 2014-2024 |
| Sweden | SE0000775298 | Active | 2011-2024 |
| Sweden | SE0001696857 | Passive | 2011-2024 |
| Sweden | SE0000582033 | Active | 2011-2024 |
| Sweden | SE0001466368 | Passive | 2011-2024 |
| Finland | FI0008800206 | Active | 2011-2024 |
| Finland | FI4000315692 | Passive | 2019-2024 |
| Sweden | SE0002756973 | Passive | 2011-2024 |
| Denmark | SE0005993078 | Passive | 2014-2024 |
| Finland | SE0005993102 | Passive | 2014-2023 |
| Norway | SE0005993110 | Passive | 2014-2024 |
| Denmark | DK0010265859 | Active | 2011-2024 |

| Domicile | ISIN | Management | Period |
|---|---|---|---|
| Denmark | DK0016060346 | Active | 2015-2024 |
| Denmark | DK0060442556 | Passive | 2013-2024 |
| Denmark | DK0060824167 | Active | 2011-2024 |
| Norway | NO0010089444 | Active | 2011-2024 |
| Norway | NO0010089402 | Active | 2011-2024 |
| Norway | NO0010105489 | Active | 2011-2024 |
| Norway | NO0010700891 | Passive | 2011-2024 |
| Norway | NO0010704265 | Passive | 2015-2024 |
| Norway | IE00B449S82 | Active | 2011-2024 |
| Finland | FI0008806617 | Active | 2011-2024 |
| Finland | FI0008800339 | Active | 2011-2024 |
| Austria | AT0000857412 | Active | 2011-2024 |
| Austria | AT0000497292 | Active | 2011-2024 |
| Japan | IE00B50MZ948 | Passive | 2011-2024 |
| Japan | GB00BF0GX360 | Passive | 2011-2024 |
| Japan | GB00BHZK8872 | Passive | 2015-2024 |
| Japan | LU0801102863 | Active | 2013-2024 |
| Japan | GB00B0119B50 | Active | 2011-2024 |
| Japan | LU0248056110 | Active | 2011-2024 |
| Japan | GB00BG03Y538 | Active | 2011-2024 |
| Australia | IE00B3YQ9180 | Active | 2011-2024 |
| Australia | LU0078775011 | Active | 2011-2024 |
| Australia | LU0261950041 | Active | 2011-2024 |
| Australia | VAN0002AU | Passive | 2011-2024 |
| Australia | AU000000VAS1 | Passive | 2011-2024 |
| Switzerland | LU0026741651 | Active | 2011-2024 |
| Switzerland | LU1159239190 | Passive | 2011-2024 |
| Switzerland | LU0054754816 | Active | 2011-2024 |
| Switzerland | DE000DWS0D27 | Active | 2011-2024 |
| Switzerland | LU0087657150 | Active | 2011-2024 |

| Domicile | ISIN | Management | Period |
|---|---|---|---|
| Switzerland | CH0356596407 | Passive | 2011-2024 |
| Baltics | LT0000990012 | Passive | 2011-2024 |
| Baltics | LTIF00000096 | Active | 2011-2024 |
| Austria | US4642862027 | Passive | 2011-2024 |
| Australia | IE00B5377D42 | Passive | 2013-2024 |
| Australia | IE00BD4TY451 | Passive | 2011-2024 |
| Canada | CA92203U1057 | Passive | 2011-2024 |
| Canada | 0P000073LN.TO | Passive | 2011-2024 |
| Canada | 0P0016LWK.TO | Active | 2011-2024 |
| Canada | 0P000070D3.TO | Passive | 2011-2024 |
| Canada | 0P000071T2.TO | Active | 2011-2024 |
| Canada | 0P000074RN.TO | Active | 2011-2024 |
| US | 4812C0464 | Active | 2011-2024 |
| US | US2332034139 | Active | 2011-2024 |
| US | US9393301067 | Active | 2011-2024 |
| US | US3998741066 | Active | 2011-2024 |
| US | US3159117502 | Passive | 2012-2024 |
| US | US9229088011 | Passive | 2011-2024 |
| US | US9229081081 | Passive | 2011-2024 |
| US | US8085098551 | Passive | 2011-2024 |
| UK | GB00B49G4H82 | Passive | 2011-2024 |
| UK | GB00B0XWNB45 | Active | 2011-2024 |
| UK | GB00B3X7QG63 | Passive | 2011-2024 |
| UK | GB00B80QFX11 | Passive | 2011-2024 |
| UK | GB0033031153 | Active | 2011-2024 |
| UK | GB00B2PLJJ36 | Active | 2011-2024 |
| Denmark | US46429B5232 | Passive | 2012-2024 |

Source: Compiled by the Author

**Appendix B: List of regions included in the dataset**

| **Region** | **Countries** |
|---|---|
| Asia | Japan |
| Europe | Austria, Denmark, Estonia, Finland, Latvia, Lithuania, Norway, Sweden, Switzerland, The United Kingdom |
| North America | Canada, United States |
| Oceania | Australia |

Source: Compiled by the Author

**Appendix C: Model (ii) results using data from 2011 to 2021**

| | Active fund alpha |
|---|---|
| Stock market efficiency | -1.000 |
| | (1.287) |
| Market risk premium | -0.233*** |
| | (0.056) |
| Market volatility | 0.060** |
| | (0.026) |
| Market risk premium (Efficiency = 1) | 0.192*** |
| | (0.069) |
| Individual fixed effects | Yes |
| Time fixed effects | Yes |
| *N* | 528 |
| $R^2$ | 0.101 |
| Adjusted $R^2$ | -0.010 |
| *Notes:* | ***Significant at the 1 percent level. |
| | **Significant at the 5 percent level. |
| | *Significant at the 10 percent level. |

Note: $N$ is reduced by $12^2$ (12 quarters for 12 regions)
Source: Compiled by the Author

## Appendix D: Model (i) and (ii) results using alternative efficiency indices

**Table D1**

*Model (i) results using IMF-WB Financial Market Index as proxy for efficiency*

| | Net quarterly return |
|---|---|
| Stock market efficiency | -3.885** |
| | (1.773) |
| Market risk premium | 0.495*** |
| | (0.023) |
| Market volatility | -0.054*** |
| | (0.013) |
| Small-minus-Big | -0.034 |
| | (0.030) |
| High-minus-Low | -0.064 |
| | (0.039) |
| Individual fixed effects | Yes |
| Time fixed effects | Yes |
| *N* | 4,400 |
| $R^2$ | 0.325 |
| Adjusted $R^2$ | 0.302 |
| *Notes:* | ***Significant at the 1 percent level. |
| | **Significant at the 5 percent level. |
| | *Significant at the 10 percent level. |

Source: Compiled by the Author

**Table D2**

*Model (ii) results using IMF-WB Financial Market Index as proxy for efficiency*

| | Active fund alpha |
|---|---|
| Stock market efficiency | -0.609 |
| | (1.438) |
| Market risk premium | -0.266*** |
| | (0.064) |
| Market volatility | 0.052** |
| | (0.021) |
| Market risk premium (Efficiency = 1) | 0.242*** |
| | (0.079) |
| Individual fixed effects | Yes |
| Time fixed effects | Yes |
| *N* | 672 |
| $R^2$ | 0.098 |
| Adjusted $R^2$ | -0.007 |
| *Notes:* | ***Significant at the 1 percent level. |
| | **Significant at the 5 percent level. |
| | *Significant at the 10 percent level. |

Source: Compiled by the Author

**Table D3**
*Model (i) using Bock and Geissel (2024) as proxy for efficiency*

| | Net quarterly return |
|---|---|
| Stock market efficiency | 0.037 |
| | (0.026) |
| Market risk premium | 0.453*** |
| | (0.022) |
| Market volatility | -0.048*** |
| | (0.018) |
| Individual fixed effects | Yes |
| Time fixed effects | Yes |
| *N* | 2,931 |
| $R^2$ | 0.334 |
| Adjusted $R^2$ | 0.307 |
| *Notes:* | ***Significant at the 1 percent level. |
| | **Significant at the 5 percent level. |
| | *Significant at the 10 percent level. |

Source: Compiled by the Author

**Table D4**
*Model (ii) using Bock and Geissel (2024) as proxy for efficiency*

| | Active fund alpha |
|---|---|
| Stock market efficiency | 0.003 |
| | (0.055) |
| Market risk premium | -0.035 |
| | (0.062) |
| Market volatility | 0.073** |
| | (0.029) |
| Market risk premium (Efficiency = 1) | -0.010 |
| | (0.008) |
| Individual fixed effects | Yes |
| Time fixed effects | Yes |
| *N* | 448 |
| $R^2$ | 0.102 |
| Adjusted $R^2$ | -0.054 |
| *Notes:* | ***Significant at the 1 percent level. |
| | **Significant at the 5 percent level. |
| | *Significant at the 10 percent level. |

Source: Compiled by the Author

**Appendix E: List of variables in the dataset**

| Variable | Coded variable name | Characteristics |
|---|---|---|
| Fund identificator | Fund.ISIN | Factor variable |
| Region | Domicile | Factor variable |
| Quarter | Quarter | Time (nominal) variable |
| Gross quarterly return of the fund | Return | Nominal variable |
| Annual total expense ratio including transaction costs and management fees | TER | Nominal variable |
| Local stock market efficiency index score | EI | Nominal variable |
| Fund management style (0: Passive; 1: Active) | Management | Binary factor variable |
| Net quarterly return of the fund (Return - TER) | Net_Return | Nominal variable |
| Passively managed funds average net return | Passive_Fund_Net_Return | Nominal variable |
| Actively managed funds average net return | Active_Fund_Net_Return | Nominal variable |
| Actively managed equity fund alpha | Return_Spread | Nominal variable |
| Fama-French Small minus Big factor returns | SMB | Nominal variable |
| Fama-French High minus Low factor returns | HML | Nominal variable |
| Market volatility, the local index standard deviation | Std | Nominal variable |
| Market return | Rm | Nominal variable |
| The risk-free rate | Rf | Nominal variable |

Source: Compiled by the Author

**Appendix F: Model (ii) results using OLS and RE methodology**

| | Active fund alpha | |
|---|---|---|
| | *OLS* | *panel linear* |
| | (1) | (2) |
| Stock market efficiency | -0.265 | -0.249 |
| | (0.417) | (0.313) |
| Market risk premium | -0.022 | -0.039 |
| | (0.017) | (0.038) |
| Market volatility | 0.011 | 0.014 |
| | (0.023) | (0.017) |
| Market risk premium (Efficiency = 1) | -0.050 | -0.065 |
| | (0.348) | (0.240) |
| Fixed effects | No | No |
| Random effects | No | Yes |
| *N* | 672 | 672 |
| $R^2$ | 0.007 | 0.016 |
| Adjusted $R^2$ | 0.003 | 0.011 |

*Notes:* ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Source: Compiled by the Author

**Appendix G: Correlation matrix**

| | TER | EI | Rm | Rf | Return | Std | SMB | HML |
|---|---|---|---|---|---|---|---|---|
| TER | 1 | -0.263 | -0.014 | -0.022 | -0.021 | 0.056 | -0.001 | -0.003 |
| EI | -0.263 | 1 | -0.029 | -0.068 | -0.016 | -0.063 | -0.031 | -0.017 |
| Rm | -0.014 | -0.029 | 1 | -0.033 | 0.846 | -0.076 | 0.298 | 0.153 |
| Rf | -0.022 | -0.068 | -0.033 | 1 | -0.060 | -0.094 | -0.217 | 0.183 |
| Return | -0.021 | -0.016 | 0.846 | -0.060 | 1 | -0.119 | 0.287 | 0.083 |
| Std | 0.056 | -0.063 | -0.076 | -0.094 | -0.119 | 1 | 0.061 | -0.114 |
| SMB | -0.001 | -0.031 | 0.298 | -0.217 | 0.287 | 0.061 | 1 | -0.037 |
| HML | -0.003 | -0.017 | 0.153 | 0.183 | 0.083 | -0.114 | -0.037 | 1 |

Notes: Variable codes used, full names in Appendix E. Pearson's pairwise methodology.
Source: Compiled by the Author

## Appendix H: Model (i) results using individual region data

**Table H1**

*Fixed effects regression on active and passive fund returns in seven regions*

| | Net quarterly return | | | | | | |
|---|---|---|---|---|---|---|---|
| | Australia | Austria | Baltics | Canada | Norway | UK | Switzerland |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Stock market efficiency | 2.766** | -10.532*** | 8.065 | 0.098 | -6.081*** | 0.275 | -11.747*** |
| | (1.387) | (1.313) | (18.254) | (0.225) | (1.068) | (0.773) | (1.018) |
| Market risk premium | 1.084*** | 0.760*** | 0.872*** | 0.961*** | 0.580*** | 1.004*** | 0.782*** |
| | (0.083) | (0.034) | (0.053) | (0.028) | (0.030) | (0.013) | (0.041) |
| Market volatility | -0.001 | -0.073*** | -0.047 | 0.016 | -0.074*** | -0.010 | -0.160*** |
| | (0.017) | (0.012) | (0.135) | (0.026) | (0.012) | (0.027) | (0.014) |
| Small-minus-Big | 0.033 | 0.239** | -0.005 | -0.013 | 0.047 | 0.254*** | 0.119 |
| | (0.041) | (0.112) | (0.020) | (0.015) | (0.071) | (0.029) | (0.075) |
| High-minus-Low | -0.107*** | -0.041*** | 0.115*** | 0.022 | -0.139*** | 0.007 | -0.317*** |
| | (0.041) | (0.012) | (0.039) | (0.022) | (0.045) | (0.065) | (0.013) |
| Fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 325 | 168 | 112 | 332 | 553 | 336 | 336 |
| $R^2$ | 0.858 | 0.894 | 0.849 | 0.966 | 0.697 | 0.905 | 0.693 |
| Adjusted $R^2$ | 0.853 | 0.890 | 0.841 | 0.965 | 0.689 | 0.903 | 0.684 |

*Notes:* ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Source: Compiled by the Author

**Table H2**

*Fixed effects regression on active and passive fund returns in five regions*

| | Net quarterly return | | | | |
|---|---|---|---|---|---|
| | Denmark | Finland | Japan | Sweden | US |
| | (1) | (2) | (3) | (4) | (5) |
| Stock market efficiency | 0.580*** | 0.815*** | 0.711*** | 0.779*** | 0.946*** |
| | (0.047) | (0.023) | (0.045) | (0.009) | (0.033) |
| Market risk premium | -0.109** | -0.284*** | -0.076*** | -0.263*** | -0.059*** |
| | (0.043) | (0.019) | (0.027) | (0.012) | (0.022) |
| Market volatility | 0.418*** | 0.034 | -0.112 | -0.284*** | 0.090** |
| | (0.087) | (0.057) | (0.074) | (0.050) | (0.037) |
| Small-minus-Big | -0.012 | 0.042*** | -0.026 | -0.166*** | -0.050* |
| | (0.045) | (0.014) | (0.144) | (0.028) | (0.029) |
| Fixed effects | Yes | Yes | Yes | Yes | Yes |
| *N* | 356 | 401 | 368 | 669 | 444 |
| $R^2$ | 0.547 | 0.785 | 0.436 | 0.834 | 0.947 |
| Adjusted $R^2$ | 0.534 | 0.779 | 0.420 | 0.830 | 0.946 |

*Notes:* ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Source: Compiled by the Author

**Resümee**

*Aktiivselt juhitud fondi lisatootluse ennustamine kasutades aktsiaturu efektiivsust*

Meelis Palm

Valides sobivat aktsiafondi mida osta, peab investor kõigepealt langetama otsuse kas valida aktiivselt juhitud või passiivselt juhitud fondi. Isegi kui fondid investeerivad laialdaselt samal turul, võib nende tootluste lõplik vahe peale haldustasusid olla märgatav. Langetamaks antud otsust, on investoril vaja raamistikku hindamaks fondide sobivust valitud investeerimisregiooniga. Üheks peamiseks majandusteooria aluskiviks indeksfondide kasvus on efektiivse turu hüpotees (EMH), mis põhineb eeldusel et aktsiaturud on keskpikas perspektiivis efektiivsed. Selles kontekstis viitab see nähtusele, kus aktsiahinnad peegeldavad kõike kättesaadavat teavet alusvara kohta kuna kauplejatel on motivatsioon parandada valehinnastamisi eeldusega, et nad suudavad teenida selle eest lisatootlust. Põhinedes eelmainitud hüpoteesile, ei tohiks ratsionaalsel investoril olla põhjust osta osakuid aktiivselt juhitud fondis, kuna keskmine aktiivselt juhitud aktsiafond ei suuda teenida turust kõrgemat tootlust keskpikas perspektiivis. Kuigi tõhusate turgude idee on laialdaselt toetust saanud, on see vastuolus aktiivsetes fondidesse paigutatud suurte summadega, mis viitab vajadusele uurida kuidas turgude informatsiooniline efektiivsus mängib rolli fondivalikus.

Eesmärgiks täita uurimislünka ning viia kokku mõlemad eelmainitud uurimissuunad, juhib see magistritöö tähelepanu sellele, kas aktsiahindade informatsiooniline efektiivsus ennustab aktiivselt juhitud fondide lisatootlust. Selleks, et täita uurimiseesmärki, kasutab see magistritöö kahte empiirilist mudelit uurimaks (i) turgude efektiivsuse rolli fonditootluses ning (ii) selle ennustusvõimet aktiivselt juhitud fondide lisatootluse suhtes tururiskipreemiaga. Mudeli tulemustele põhinedes saab järeldada, et aktsiaturu suhteline efektiivsus on statistiliselt oluline ennustaja fonditootluses ning ennustab aktiivselt juhitud fondide tundlikkust tururiskipreemiale. Selle põhjal saab väita, et aktsiaturu tõhususel on oluline roll aktsiafondi valikus ning et see saab aidata ratsionaalsel investoril langetada parem fondivalik. Nõnda aitab see magistritöö kaasa fondide vahelises valikus ning täidab lünka varasemas kirjanduses.

Võtmesõnad: aktsiaturg, finantsmudelid, finantsturg, käitumuslik majandus

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