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Chasing returns: Are Swedish funds outperforming their benchmarks?

By

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ABSTRACT

This study investigates the performance dynamics of Swedish mutual funds, with a particular focus on the impact of active management, as measured by tracking error, on risk-adjusted returns (Sharpe ratio). The findings reveal a consistent negative correlation between tracking error and Sharpe ratio, indicating that higher levels of active management are associated with poorer performance relative to benchmarks among Swedish mutual funds. This challenges the traditional notion that active management can deliver superior returns. For investors, the findings underscore the need to reconsider the value proposition of actively managed funds in favor of passive strategies with lower fees. For fund managers, the results suggest prioritizing risk management strategies that minimize deviations from benchmarks. Future research should continue to explore these dynamics in a Swedish context to provide a more comprehensive view of mutual fund performance.

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Abbreviations

EMH - Efficient market hypothesis

E-V - Expected return-variance

NAV - Net asset value

MPT - Modern portfolio theory

1. Introduction

Fifty years ago, the investment landscape was vastly different from what we see today. Active management reigned supreme, with investors believing that skilled managers could consistently beat the market by identifying undervalued securities. Access to financial information was not as widespread or instantaneous as it is today, and investors relied heavily on traditional financial media such as newspapers, magazines, and television for market updates and analysis. In this environment, careful research and analysis were believed to be the keys to success, and the efficient market hypothesis (EMH) was often challenged. (Malkiel, 2003)

In 1976, John Bogle revolutionized the investment world by introducing the first passively managed fund, the Vanguard 500 Index. Unlike traditional actively managed funds, which aimed to outperform the market, Bogle's innovation was designed to simply track the performance of the market. This marked a significant shift in investment philosophy, challenging the notion that active management was the superior strategy. Over time, this approach gained traction, reshaping the investment landscape.

By 2017, approximately 41 percent of all managed capital was held in passive investment strategies, according to BlackRock (2017). This rise of passive investing can be attributed to several factors, with the growing acceptance of the efficient market hypothesis being paramount. The EMH, proposed by Eugene Fama in 1970, suggests that asset prices reflect all available information, making it difficult for investors to consistently outperform the market through active management. As investors became more aware of the limitations and costs of active management, they turned to passive strategies that aim to replicate market returns at a lower cost. Passive investing offers simplicity, lower fees, and the assurance of market-wide returns without the need for constant monitoring and active decision-making. This shift in investor preference has led to a significant transformation in the investment industry, with passive investing now playing a major role in many portfolios.

The debate surrounding active mutual funds versus passive index funds persists in the investment literature. The question of whether active management, with its focus on outperforming the market through stock selection and timing generates excess return relative to that of a benchmark index–that is, alpha–remains unresolved. Consequently, this study aims to investigate the Swedish investment landscape to determine whether Swedish mutual funds outperform or underperform their benchmark indices.

1.1 Aim of the study

The objective of this research paper is to investigate the influence of active management on the performance of Swedish mutual fund portfolios. Utilizing comprehensive fund data sourced from Fondbolagens förening's NAV-centre, alongside corresponding benchmark indices obtained from Bloomberg, the study aims to examine the impact of active management on mutual fund performance relative to their benchmark index, defined herein as Sharpe ratio, within the Swedish stock exchange.

The primary objective of this study is to clarify the performance dynamics of Swedish mutual fund portfolios amidst contradicting scholarly opinions on the effectiveness of active management. By doing so, it seeks to enhance our understanding of market efficiency in the context of the Swedish stock exchange.

This will be through the following research question:

> Does tracking error impact sharpe ratio among mutual funds in Sweden?

1.2 Scope of the study

Previous research on active management has often factored in fees and other expenses to determine a more accurate alpha. However, due to the scale and scope of this study, which includes nearly all actively managed mutual funds in Sweden, this aspect will not be incorporated. Instead of precisely examining the investor's gains or losses from investing in an actively managed fund in Sweden, our aim is to determine whether active management on the Swedish stock exchange positively or negatively impacts returns relative to benchmark indices. To further enhance this analysis, additional robustness testing will be conducted to investigate whether these relationships vary across different macroeconomic conditions and cycles.

1.3 Definitions

This study examines the correlation between returns and active management, necessitating a clear definition of passive and active portfolio investments.

Passive investment, as defined in this study, involves replicating the return of an index by purchasing, holding, and weighting the portfolio according to the underlying index proportions, as outlined by Cremers and Petajisto (2009).

Active investment, on the other hand, is characterized by deviations from passive strategies (Cremers & Petajisto, 2009). This involves behavior that deviates from any form of underlying benchmark index, and this study will measure how the degree of deviation affects returns. Depending on the desired measure of deviation, this can be calculated in various ways. This method will measure active investment through tracking error, which is explained more in-depth in Section 3.2.1.

The study encompasses 90 Swedish mutual funds, selected based on their (1) domicile in Sweden, and (2) investment in Swedish stocks. All funds classified as index funds have been excluded, however, the sample utilized comprises both more and less actively managed funds.

1.4 Thesis outline

We will start by reviewing existing literature concerning fund selection strategies and their effects on portfolio performance, with particular emphasis on tracking error. Drawing from previous studies, we will develop hypotheses to guide our empirical analysis. Our analysis will be based on a carefully selected sample of funds and corresponding benchmark indices, spanning a defined time frame. Tracking error, and other relevant data will be gathered and analyzed and additional testing will be conducted to ensure robustness.

The data used in the study will then be presented and we will provide an explanation of all statistical procedures undertaken prior to hypothesis testing. Descriptive statistics for the final dataset will be presented. Following this, we will outline the methodology for the regression analysis, including the econometric rationale behind model specifications for hypothesis testing.

The main findings are presented, followed by supplementary results to evaluate the robustness of the outcomes under various conditions. Subsequent to the results section is the discussion, and lastly the final conclusions of the paper are presented.

2. Literature review

2.1 Background and theory

2.1.1 The efficient market hypothesis

In 1970 Fama published a paper on the efficient market hypothesis (EMH), which changed the then current sentiment about investing and fund investing. Prior to this publication, the prevailing belief was rooted in the idea that markets were inefficient, and investors could profit by exploiting market imperfections such as information asymmetry and various forms of arbitrage.

Fama (1970) challenged this notion by asserting that in an efficient market security prices fully incorporate all available information, and categorizes three forms of market efficiency: weak form efficiency, where security prices reflect all historical market data; semi-strong form efficiency, where security prices reflect all publicly available information; and strong form efficiency, where security prices incorporate both public and private information. This implies that even insider information is fully incorporated into prices, rendering it impossible for investors to gain an advantage by trading on any information, regardless of its nature.

Based on Fama's (1970) conclusion that security returns follow a random walk, he argues that the sophisticated analysis characteristic of active fund management cannot effectively predict future returns.

2.1.2 Modern portfolio theory

In 1952, Markowitz laid the theoretical groundwork for portfolio selection, initiating the development of modern portfolio theory, which stands as one of the most influential and widely applied methodologies for portfolio optimization. Subsequently, this theory underwent continuous refinement, giving rise to additional methods such as the Sharpe ratio (Sharpe, 1966), Treynor ratio (Treynor, 1965), and Jensen's alpha (1968).

Markowitz's paper (1952) offers valuable insights into the theoretical underpinnings of portfolio selection, emphasizing the necessity for a systematic approach that integrates statistical techniques with practical judgment. He critiques the conventional rule of maximizing discounted expected returns, arguing against its effectiveness as a guiding principle for investment behavior. Instead, he advocates for considering expected return as desirable and variance of return as undesirable when constructing a portfolio, i.e. balancing risk with reward. This principle, termed the "expected returns-variance of returns" rule, operates under the assumption of investor risk aversion.

Markowitz (1962) also emphasizes the importance of diversification in portfolio selection to reduce risk, highlighting that the E-V (expected return-variance) principle leads to efficient portfolios that are typically diversified. He suggests that investors should aim for the "right kind" of diversification by including a mix of securities from different industries to mitigate the impact of industry-specific risks.

2.2 Literature review

The current scholarly literature on mutual fund performance presents a conflicting narrative. While some studies suggest that actively managed mutual funds outperform their benchmarks over the long term, others argue that the majority of mutual funds fail to consistently beat the market after accounting for fees and expenses. Additionally, there is ongoing debate about whether past performance is indicative of future results, further complicating the evaluation of mutual fund performance. In the following section, we will compile and compare current literature on the subject.

2.2.1 Evidence of underperforming benchmarks

One of the foundational pillars in the literature of asset management traces back to Jensen's seminal work in 1968. In his paper, Jensen laid the groundwork for understanding the efficacy of mutual funds in predicting security prices, and found that on average, mutual funds demonstrated limited ability to forecast security prices accurately enough to outpace a passive investment strategy.

Jensen's findings debunked the prevailing notion that individual funds, even after accounting for expenses, significantly outperformed the broader market due to managerial skill rather than sheer luck. Despite the widespread belief in the prowess of fund managers, Jensen's empirical evidence painted a picture of muted success in consistently beating the market.

However, Jensen also highlighted a crucial aspect: while the evidence might not support the notion of consistent outperformance, mutual funds still provided a socially desirable service to investors, particularly in terms of risk management. This acknowledgment underscores the nuanced role that mutual funds play in investment landscapes, even if their ability to consistently outperform market benchmarks was proved questionable.

Building upon Jensen's (1968) work, Malkiel's (1995) study further cemented the understanding of mutual fund performance dynamics. Malkiel's (1995) analysis, spanning two decades from 1971 to 1991, corroborated Jensen's findings and added new insights into the persistent challenges faced by mutual funds.

Malkiel (1995) did not only confirm the systematic underperformance of mutual funds relative to their benchmarks but also shed light on the phenomenon of survivorship bias. This bias, wherein poorly performing funds are more likely to be closed or merged with other funds, skews the perceived performance of the remaining funds. Malkiel (1995) revealed that this bias tended to be more severe than previously estimated, emphasizing the need for careful consideration when interpreting mutual fund performance data.

Fama and French (2010) discovered evidence of both under- and overperformance, indicating non-zero true alpha, in the extreme cases of mutual fund estimates. However, they also observed that the aggregate portfolio of actively managed US mutual funds closely resembled the market portfolio, implying the absence of true alpha at a broader level. Nonetheless, the high costs associated with active management serve to dampen the overall returns to investors.

2.2.2 Evidence of overperforming benchmarks

While some studies have argued that asset management strategies lack significance and profitability, others refute this claim by presenting evidence of managerial skill surpassing market performance.

Avramov and Wermers (2006) investigated US equity mutual funds spanning from 1975 to 1994, focusing on manager skills, fund risk loadings, and benchmark returns. Their findings revealed the significance of predictability-based strategies within mutual funds, resulting in higher Sharpe ratios. That is, strategies aimed at predicting performance through different qualitative metrics proved to be vital in investigating . Notably, predictability in manager skills emerged as the primary driver of performance. They demonstrated that this predictability enabled funds to outperform the Fama-French benchmark by 2 to 4% through timing industries over business cycles and an additional 3 to 6% through stock selection. Their study also emphasized the crucial role of industry screening and selection in identifying outperforming mutual funds.

Chen et al. (2000) examined the stock selection skills of US mutual funds over the same period, from 1975 to 1995. Their research echoed Avramov and Wermers' findings, indicating a discernible ability among mutual funds to effectively select stocks. Notably, stocks actively purchased by funds yielded significantly higher returns than those actively sold.

However, Chen et al. also uncovered a temporal limitation associated with mutual funds' stock selection prowess. Despite initially demonstrating superior abilities, the advantage of mutual funds in selecting stocks appeared to diminish over time. Specifically, stocks bought by funds outperformed those sold only during the first year following the trades, suggesting a temporal constraint on the efficacy of mutual funds' information advantage.

In line with the conclusions drawn by Chen et al. (2000), Cuthbertson et al. (2010) examined the performance dynamics of primarily US and UK stocks. Their study revealed that a minority of top-performing funds, roughly 0-5%, exhibited non-zero alpha after adjusting for fees. Additionally, while a notable portion of mutual funds underperformed their respective markets, the majority presented zero alpha.

Consistent with the findings of Chen et al., Cuthbertson et al. also highlighted the persistence of fund underperformance over time. They observed a recurring pattern whereby funds that historically lagged behind their benchmark indices tended to perpetuate this trend, indicative of a common behavioral pattern among mutual fund managers.

Hendricks et al. (1993) introduced the concept of the "hot hands" strategy as a lens through which to explore the predictability of short-term managerial skills in mutual fund management. Their inquiry revealed that mutual funds adopting a growth-oriented investment approach exhibited persistent behavior over the short term. Specifically, recent top-performing funds demonstrated sustained superior performance, while underperforming funds experienced a notable decline relative to standard benchmark metrics.

In a more recent study by Cremers and Petajisto (2009), a new measure of active management, known as active share, is introduced to complement the concept of tracking error and provide a more nuanced evaluation of stock selection and factor timing skills among mutual fund managers. Active share serves as a more precise metric for assessing stock selection strategies. The researchers observed that funds with higher active shares tended to demonstrate stronger and more persistent performance over time. Specifically, they found that actively managed funds with lower active shares consistently underperformed their benchmarks, whereas those with higher levels of activity exhibited superior performance, indicating a positive correlation between active share and fund performance.

As evident, the bulk of existing research primarily centers on mutual funds in the US, occasionally extending to the UK. However, there remains a notable scarcity of studies focusing on the European market, particularly the Swedish market. This knowledge gap underscores the need for further investigation into the dynamics of Swedish mutual funds. Consequently, this paper seeks to contribute to the existing literature by providing insights specifically tailored to the Swedish mutual fund landscape, thereby adding to our understanding of mutual fund behavior and performance within the more regional context.

3. Data

3.1 Sample size and population

The population of this study consists of a selection of 90 funds, which were refined from an initial pool of 130 funds. The selection process was based on Fondbolagens Förening's list of Swedish actively managed funds, which was subsequently revised and adjusted to account for data availability.

From the initial pool of 130 funds, NAV-center distributed data for 100 of these funds. Subsequently, these 100 funds were matched to a benchmark index. Information on benchmark indices was primarily obtained from Avanza (investor relations material). Due to constraints related to data availability for matching benchmark indices and the time aspect, the dataset was further reduced to ensure balanced regression material.

Table A3.1 presents a list of all included funds. The data was collected on a daily basis, corresponding to trading days.

3.1.1 Fund Selection and benchmark index

Benchmark indices were allocated based on each respective fund's match to a benchmark index. However, due to data unavailability, the replacements were made in accordance with Table 3.1.1. The final benchmark index allocation is displayed in Table A.3.1.

Table 3.1.1. Benchmark index replacements

Original Benchmark	Replaced with
MSCI Sweden Small Cap NR SEK	NASDAQ OMX Small Cap Sweden GI
MSCI Sweden NR SEK	NASDAQ OMX Stockholm Benchmark Cap GI
MSCI Sweden Value Index	NASDAQ OMX Stockholm 30
Morningstar Sweden TME NR EUR	NASDAQ OMX Stockholm Benchmark Cap GI
SIX Sweden SRI Index GI	SIX Portfolio Return Index
NASDAQ OMX Stockholm All-Share Cap GI	NASDAQ OMX Stockholm Benchmark Cap GI

3.1.2 Time frame

All available data on all Swedish actively managed funds was obtained from NAV-center. The initial dataset comprised daily observations spanning the period from January 1, 2000, to January 25, 2024. The data was subsequently grouped on a weekly basis, where all data points represent weekly averages.

3.2 Measures of Active Management

Active management and its impact on returns can be broken down into two fundamental aspects of investing: stock selection and tactical asset allocation (Fama, 1972; Brinson, Hood & Beebower, 1986; Daniel et al., 1997). Stock selection involves identifying stocks that outperform a benchmark index while maintaining systematic risk at a constant level, which entails controlling for factors like market beta, book-to-market ratio, and industry. Tactical asset allocation, on the other hand, focuses on adjusting the composition of broader portfolios over time (Fama, 1972).

The conventional method of evaluating active management involves measuring the volatility of tracking error, which assesses a mutual fund's overall deviation from its benchmark index. Subsequent studies, such as those by Cremers and Petajisto (2009), have introduced active share as an additional measure of active management. However, due to the scale and scope of this study, only one measure of active management has been included, namely tracking error, because of its applicability to larger datasets.

3.2.1 Tracking error

Tracking error is commonly used as a way to track a fund's performance in relation to its benchmark index and is defined as the standard deviation of the difference in return between a fund and its benchmark index in a time series (Grinold and Kahn, 1999):

$$Tracking\ error_{i,t} = SE[ln(R_{i,t}) - ln(R_{benchmark,t})]$$

An active manager wants an expected return higher than the benchmarks index while keeping a low tracking error, i.e. a low volatility on returns. Since tracking errors include measuring the covariance matrix of returns, the measurement is strongly reliant on the relation between different asset weightings, making it a reasonable proxy for tactical asset allocation as well as stock selection (Cremers & Petajisto, 2009).

3.3.2 Included control variables

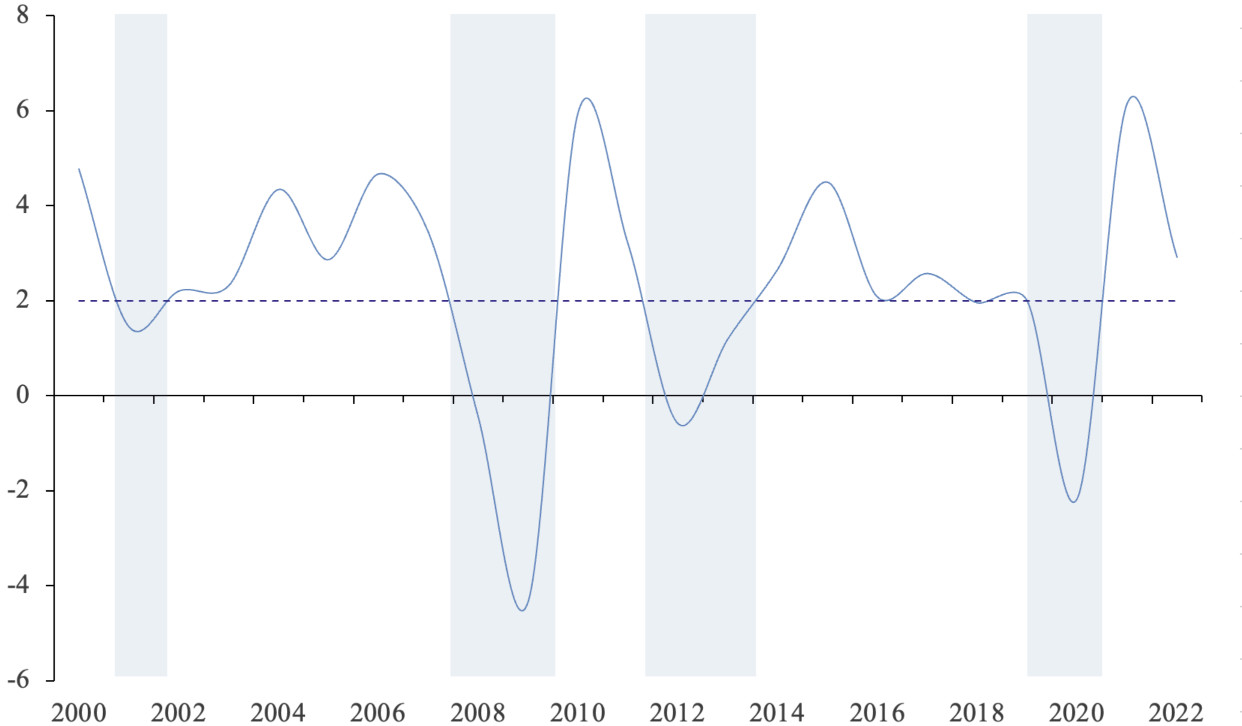
Previous studies have found evidence of variability in the impact of active management on performance. In 2001, Kosowski conducted a study on the performance of US mutual funds, revealing that US mutual funds tend to perform better in recession periods when investors' marginal utility of wealth is high. The results show asymmetries in time-variation, with growth/income and balanced/income funds outperforming aggressive growth and growth funds in recessions.

Similarly, research by Ingersoll (1987) and Cochrane (2001) has highlighted the importance of recessions and booms in influencing investor preferences and asset prices. Investors are more concerned about their portfolios' performance in certain economic conditions, leading to variations in asset prices and risk premiums.

To address this, and to mitigate potential omitted variable bias in our regression analysis, we have included macroeconomic controls in the form of dummy variables. Specifically, we have absorbed all year-specific effects over time into the regression by incorporating year-specific fixed effects. Additionally, we have added dummy variables representing different macroeconomic periods to our sample. These dummy variables are based on whether GDP growth exceeds or falls below the inflation rate of 2%, thereby representing periods of recessions and booms in accordance with the ideas put forth by Kosowki (2001). The rationale behind including these controls is to distinguish fund performance relative to its benchmark during periods of economic growth versus economic disparity, as well as also absorbing yearly effects which does not necessarily constitute an economic period in itself. By accounting for macroeconomic conditions, we aim to better understand how fund performance varies across different economic environments.

Swedish GDP growth, along with the included dummy variables, can be observed in Figure 3.3.2 as well as Table 3.3.2.

Figure 3.3.2. Swedish GDP growth (annual %)



Source: World Development Indicators (n.d.)

Table 3.3.2. Dummy variables

Dummy	Categorization	Comment
2001-2002	Recession	
2002-2007	Boom	
2007-2009	Recession	The great financial crisis
2009-2011	Boom	
2011-2013	Recession	Debt Crisis
2013-2019	Boom	
2019-2020	Recession	Covid-19
2020-2023	Boom	

Source: World Development Indicators (n.d.)

Additionally, for further robustness testing, interaction variables in accordance with equation 3.3.2 have been included.

Equation 3.3.2

$$Interaction_p = Tracking\ error_p \cdot Dummy_p$$

The interpretation of the interaction variable is as follows: it demonstrates how the impact of tracking error on the Sharpe ratio changes as the dummy variable transitions from zero to one and enters period p. In other words, a significant positive beta coefficient for the interaction term indicates that during a particular time period (when the dummy variable equals one), the effect of tracking error on the Sharpe ratio is positively amplified.

By incorporating these combined variables, the aim is to effectively isolate all macroeconomic effects associated with specific economic periods and examine whether they significantly influence the Sharpe ratio, as well as its interaction with tracking error. As mentioned earlier, the model has also accounted for all yearly fixed effects, although they will not be presented in the results.

3.4 Descriptive statistics

Table 3.4 presents an overview of the descriptive statistics of the paper. The number of observations has been cleaned from approximately 270 000 and made weekly, causing the number of observations to go from exactly 269 342 to 47 608.

Table. 3.4 Descriptive statistics

Variable	Obs	Mean	Std. dev.	Min	Max
Mean NAV return (ln)	47,608	5.53	0.52	3.31	6.31
Mean Benchmark return (ln)	47,608	6.83	0.64	5.02	7.75
Sharpe Ratio	47,608	9.11	8.71	-0.02	121.70
Tracking error	47,608	3.76	3.13	0.00	123.86
2001-2002	47,608	0.02	0.14	0.00	1
2002-2008	47,608	0.16	0.37	0.00	1
2008-2009	47,608	0.07	0.25	0.00	1
2009-2011	47,608	0.11	0.32	0.00	1
2011-2013	47,608	0.12	0.33	0.00	1
2013-2019	47,608	0.37	0.48	0.00	1
2019-2020	47,608	0.08	0.27	0.00	1
2020-2023	47,608	0.30	0.46	0.00	1
Interaction 2001-2002	47,608	0.00	0.00	0.00	0.03
Interaction 2002-2008	47,608	0.00	0.00	0.00	0.12
Interaction 2008-2009	47,608	0.00	0.00	0.00	0.05
Interaction 2009-2011	47,608	0.00	0.00	0.00	0.05
Interaction 2011-2013	47,608	0.00	0.00	0.00	0.07
Interaction 2013-2019	47,608	0.00	0.00	0.00	0.04
Interaction 2019-2020	47,608	0.00	0.00	0.00	0.03
Interaction 2020-2023	47,608	0.00	0.00	0.00	0.04

4. Methodology

This section explains the methodology employed in the study, encompassing the research design for both the primary regression analysis and further robustness regression testing. Additionally, it includes the econometric analysis conducted preceding the execution of the regression analysis.

4.1 Research design

The research design consists of a panel data regression analysis where the time dimension consists of daily data for the years 2000-2023 and the cross-sectional dimension consists of XX funds. The model is in accordance with theory of tracking error (SOURCE), Sharpe ratio (Sharpe, 1966) and based on previous research conducted on the performance of mutual funds (Cremers & Petajisto, 2009). The model is shown in Equation 4.1.1.

Equation 4.1.1.

$$Sharpe\ Ratio_{i,t} = \alpha_i + \beta_{i,1} Tracking\ error_{i,t} + \beta_{i,2} controls_i + \varepsilon_{i,t}$$

The dependent variable, in this case, is the Sharpe ratio of the funds investigated in the paper and is derived as is displayed in Equation 4.1.2.

Equation 4.1.2.

$$Sharpe\ Ratio_{i,t} = \frac{ln(R_{i,t}) - ln(R_{f,t})}{\sigma_{i,t}}$$

Where $R_{i,t}$ is the return of the underlying fund in time t, $R_{f,t}$ is the risk free rate based on the Swedish 10 year treasury bond rate, and $\sigma_{i,t}$ is the standard deviation of the natural logarithm of the fund return, estimated on a weekly basis. The natural logarithm of both measures of return have been taken as they are dealt with in absolute terms.

The Sharpe Ratio measures the excess return earned per unit of risk taken. A higher Sharpe Ratio essentially indicates a better risk-adjusted return (Sharpe, 1966).

The independent variable is the measure tracking error, and is derived as is displayed in Equation 4.1.3.

Equation 4.1.3.

$$Tracking\ error_{i,t} = SE[ln(R_{i,t}) - ln(R_{benchmark,t})]$$

Where $R_{benchmark,t}$ is the return of the underlying benchmark, and the standard deviation is taken on a weekly basis.

In addition to this, robust clustered standard errors are added to the regression model to address the problem of heteroscedasticity.

To further strengthen the analysis, control variables have been included as discussed in section 3.3.2 . These take the form of dummy variables aimed to isolate macroeconomic effects.

4.2 Additional robustness testing

Additional robustness testing is conducted to assess the robustness of the results. This is done in the context of adding interaction variables to the original model as displayed in Equation 4.2.1.

Equation 4.2.1.

$$Sharpe\ Ratio_{i,t} = \alpha_i + \beta_{i,1} Tracking\ error_{i,t} + \beta_{i,2} controls_i + \beta_{i,3} interaction_i + \varepsilon_{i,t}$$

Adding additional variables may help as a robustness test. For example, if the results change significantly when different control variables are included, it may indicate that the original model was misspecified. This will also shed light on whether the primary relationship between tracking error and the Sharpe ratio varies across different economic periods.

Further information on the interaction terms of their interpretation can be found in section 3.3.2 Included control variables.

4.3 Determining fixed of random effect

4.3.1 Hausman test

To assess whether the variables in the sample contain individual or time specific effects, a Hausman test has been conducted. The Hausman test poses the null hypothesis that there is no endogeneity present in the sample, implying that the unique errors are not correlated with the regressor. Rejecting the null hypothesis therefore implies that there are unobserved individual-specific effects that are correlated with the regressors - calling for a fixed effect model.

The fixed effect model takes into account fund-specific characteristics that are constant over time and may affect the dependent variable. By including these fixed effects, the model controls for unobserved heterogeneity among individuals (the funds), allowing for more accurate estimation of the relationships between the independent and dependent variables.

The results are shown in Table 4.3.1.

Table 4.3.1. Hausman test results

Model	p-value[a]	Suitable panel model
Base Model	0.0000	Fixed effect model
Extended Model	0.0000	Fixed effect model
Interaction Model	0.0000	Fixed effect model

a. A p-value > 0.05 (significance level) indicates a random effect model is most suitable for the dataset. A p-value < 0.05 (significance level) indicates a fixed effect model is most suitable for the dataset.

4.4 Addressing economic and statistical bias

4.4.1 Autocorrelation

Autocorrelation refers to the correlation between the residuals of the regression model across different observations and hence, it is a violation of the assumption that the errors are independent of each other.

Autocorrelation can occur when the observations are collected over time or across space in a way that there is some inherent correlation between consecutive observations. To test for autocorrelation, a Woolridge test was conducted. The Wooldridge test, set forth by Wooldridge (2010), is an extension of the previously established Durbin-Watson test, more suitable for time series data (Durbin and Watson (1950, 1951). The results of the Woolridge test indicated no evidence of autocorrelation.

4.4.2 Heteroscedasticity

Heteroscedasticity is a phenomenon characterized by the variability of the error term in a regression model not being constant across all levels of the independent variables. Put simply, the variance of the error term changes as the values of the independent variables change.

In panel regressions, which involve data with both cross-sectional and time-series dimensions, heteroscedasticity can arise due to various factors such as differences in volatility across entities or over time.

To test for heteroscedasticity, we conducted a Breusch-Pagan test, which involves regressing the squared residuals from the panel regression on the independent variables and their squares with the null hypothesis that no heteroscedasticity exists in the model. The results are presented in Table 4.4.1.

Table 4.4.2. Breusch-Pagan test results

Model	p-value	Implication
Base Model	0.000	Heteroscedasticity
Extended Model	0.000	Heteroscedasticity
Interaction Model	0.008	Heteroscedasticity

As the results from all models show significant statistical results, all models are considered heteroscedastic. To mitigate these issues, robust standard errors have been included in the model. These standard errors adjust for heteroscedasticity and provide more reliable inference.

4.3.4 Stationarity

Stationarity refers to a property of time series data where the statistical properties such as mean, variance, and autocovariance remain constant over time. In other words, the data does not exhibit any long-term trends or systematic patterns that change over time.

To assess stationarity, a unit root test was performed using the Augmented Dickey-Fuller framework (or Phillips-Perron). The ADF test examines the null hypothesis of a unit root, implying a non-stationary series. We reject this hypothesis, suggesting that the variable is stationary.

5. Empirical findings

The following section presents empirical findings, including results from a Pearson correlation matrix, the main outcomes from the panel regression analysis, and additional results from further regression testing.

5.1 Bivariate analysis

Table 5.1 displays the results of the bivariate analysis, where a Pearson correlation test has been conducted. As shown, the Sharpe ratio exhibits a significant negative correlation with tracking error at a significance level of 1%. This implies that analyzing the direct correlation, without controlling for other factors, provides an indication of the importance of tracking error on the Sharpe ratio.

Table 5.1
Pearson correlation matrix.

	(1)	(2)
(1) Sharpe Ratio	1.0000	
(2) Tracking Error	-0.2201***	1.0000

***, **, * Significance at 1, 5 and 10 percent respectively

5.2 Main results

The main results of the study are displayed in Table 5.1.

Table 5.2
Main results.
Column (1) displays the regressions results of the Base model with only the independent variable tracking error plotted against the dependent variable Sharpe ratio. Column (2) displays the results when the dummy variables based on different economic cycles are included, and column (3) further shows the results when the interaction terms have been added.

	(1) Base	(2) Extended	(3) Interaction
Tracking error	-0.38*** (0.04)	-0.38*** (0.04)	-0.30*** (0.05)
2001-2002		-4.66*** (0.47)	-4.52*** (0.45)
2002-2008		-7.91*** (0.62)	-9.10*** (0.67)
2008-2009		3.90*** (0.46)	3.61*** (0.50)
2009-2011		-7.35*** (0.57)	-8.06*** (0.68)
2011-2013		4.33*** (0.48)	4.55*** (0.51)
2013-2019		-2.86*** (0.50)	-2.30*** (0.58)
2019-2020		9.07*** (0.34)	10.28*** (0.46)
2020-2023		-0.54* (0.22)	0.18 (0.27)
Interaction 2001-2002			-0.06 (0.06)
Interaction 2002-2008			0.05 (0.05)
Interaction 2008-2009			0.11** (0.04)
Interaction 2009-2011			0.02 (0.07)
Interaction 2011-2013			0.05 (0.05)
Interaction 2013-2019			-0.34*** (0.07)
Interaction 2019-2020			-0.27** (0.10)
Interaction 2020-2023			-0.22*** (0.06)
Constant	5.07*** (0.40)	9.73*** (0.28)	9.52*** (0.28)
Observations	47 608	47 608	47 608
Fixed effects	Yes	Yes	Yes
Clustered standard errors	Yes	Yes	Yes
R^2	0.21	0.21	0.22

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results show that there is a negative significant correlation between tracking error and sharpe ratio throughout all tested models.

Column (1) includes the result from the univariate regression where tracking error has been plotted against Sharpe ratio. As visible, there is a negative relation between Sharpe ratio and tracking error ($\beta = -0.38$) with a significance of 0.01. A negative coefficient for tracking error in the model (-0.38) suggests that an increase in tracking error is associated with a decrease in the Sharpe Ratio, indicating poorer performance relative to risk. This implies that higher levels of tracking error, reflecting greater deviation from the benchmark index, are linked to lower Sharpe Ratios, which signifies less favorable risk-adjusted returns for the mutual fund.

Therefore, based on the coefficient estimate, mutual funds with higher tracking errors are expected to exhibit lower Sharpe Ratios, indicating inferior performance relative to those with lower tracking errors.

For the Base model, the R^2 value is 0.21, which means that approximately 21% of the variation in the Sharpe Ratio can be explained by the variables included in the model. This indicates a moderate level of explanatory power, suggesting that the independent variables collectively account for 21% of the variation, and that a substantial portion of the variation in the Sharpe Ratio remains unexplained by the model. However, this could be attributed to the fixed effects model used in the regression. A fixed effects model used in this regression can improve the explanation of residual variation by removing the influence of unobserved, time-invariant factors. If these factors account for a significant portion of the total variation, the R^2 within the fixed effects model can appear lower because it only considers the variation around the fixed effects.

Column (2) presents the results of the extended regression model, wherein tracking error is regressed against the Sharpe ratio along with control variables in the form of period dummies. Notably, the analysis reveals a negative relationship between the Sharpe ratio and tracking error ($\beta = -0.38$), with a significance level of 0.01. Furthermore, all included control variables exhibit significant correlations with the dependent variable, indicating that each period considered in relation to the Sharpe ratio significantly influences its value. This suggests substantial disparities in the Sharpe ratio across different time periods, as captured by the dummy variables.

Interestingly, the direction of the coefficient does not consistently align with the direction of GDP growth that the variables represent. In fact, it appears that during three out of four recessions, the Sharpe ratio is statistically significantly higher compared to other periods, whereas during four out of four boom periods, the Sharpe ratio is statistically significantly lower. This implies that managerial skill within Swedish mutual funds are better during recessions rather than booms.

Column (3) presents the results of the interaction regression model, wherein tracking error is regressed against the Sharpe ratio along with control variables in the form of period dummies as well as their interaction term with tracking error. Once again, the analysis reveals a negative relationship between the Sharpe ratio and tracking error ($\beta = -0.30$), however slightly muted as compared to previous models ($\beta = -0.38$), with a significance level of 0.01. All included control variables exhibit similar correlations as they did in the extended model.

Between the periods of 2008-2009 and 2013-2023, there is a consistently observed statistically significant correlation between the interaction term and the Sharpe ratio, with significance levels ranging from 0.01 to 0.05. Notably, during the financial crisis of 2008-2009, a positive and significant correlation ($\beta = 0.11$) was observed between the interaction term and the Sharpe ratio, with a significance level of 0.05. This suggests that amidst the financial crisis, funds with higher tracking errors, signifying greater deviation from the benchmark index, exhibited significantly better performance in terms of Sharpe ratio compared to less active funds during other periods.

Conversely, a negative correlation was noted during the subsequent years between 2013-2024, where the interaction between variables and the Sharpe ratio demonstrated the most substantial correlation. This negative correlation persisted with significance levels ranging from 0.05 to 0.01 and coefficient values falling between -0.22 and -0.34. This trend indicates that since 2013, the tracking error term's influence on the Sharpe ratio has been adverse, resulting in a decline in performance. Essentially, during the period of 2013-2023, funds with higher tracking errors experienced significantly inferior Sharpe ratio performance compared to more actively managed funds, reflecting a negative correlation. This interpretation suggests that active management has not significantly contributed to the performance of Swedish mutual funds over the past decade compared to earlier periods. However, it is noteworthy that this correlation seems to be diminishing over time.

The Extended and Interaction models also display R^2 values of 0.21 and 0.22, respectively. These values indicate a similar level of explanatory power compared to the Base model, suggesting that the additional variables included in the Extended and Interaction models do not substantially improve the overall explanatory power of the regression models. This is an indication of lack of further explanatory variables in the model.

6. Discussion

6.1 Summary of results

In summary, the analysis rejects the null hypothesis that tracking error has no impact on the Sharpe ratio among Swedish mutual funds. Across all tested models, a negative significant correlation between tracking error and Sharpe ratio is consistently observed. Specifically, the univariate regression (Column 1) reveals a negative relationship between Sharpe ratio and tracking error ($\beta = -0.38$) with a significance level of 0.01. This indicates that higher levels of tracking error are associated with lower Sharpe ratios, suggesting inferior risk-adjusted returns for the mutual funds.

Furthermore, the extended regression model (Column 2) and interaction regression model (Column 3) both confirm this negative relationship between Sharpe ratio and tracking error, albeit with slightly varied coefficients. Notably, the interaction model identifies significant correlations between the interaction term and Sharpe ratio during specific periods, such as the financial crisis of 2008-2009 and the subsequent years from 2013-2024. During the crisis, funds with higher tracking errors exhibited significantly better Sharpe ratio performance, whereas in the later period, higher tracking errors were associated with significantly inferior Sharpe ratio performance.

Overall, while active management does not appear to have significantly contributed to Swedish mutual fund performance over the past decade compared to earlier periods, it is important to note that this correlation is diminishing over time. The R^2-values across all models indicate a moderate level of explanatory power, suggesting that the included variables collectively account for a substantial portion of the variation in the Sharpe ratio.

6.2 Implications of results

6.2.1 Main implications

The implications of the results hold significant importance in deepning our understanding of the Swedish investment landscape and how active management affects return.

The finding that higher tracking errors are associated with lower Sharpe ratios aligns with previous studies by Jensen (1968) and Malkiel (1995), which demonstrated the systematic underperformance of actively managed funds relative to benchmarks. Jensen's seminal work showed that mutual funds, on average, do not outperform the market after accounting for expenses, suggesting that active management often fails to add value. Malkiel further corroborated these findings, highlighting the prevalence of survivorship bias in mutual fund performance studies and emphasizing the challenges active managers face in consistently beating the market.

Firstly, this mitigates the incentives for investors to invest in actively managed funds in Sweden. The consistent underperformance of funds with higher tracking errors suggests that active management may not deliver the superior returns necessary to justify its higher fees. Consequently, investors might reconsider the value proposition of actively managed funds and instead turn to passive investment strategies with lower fees.

For fund managers, this implies that they should prioritize risk management strategies that minimize deviations from benchmark indices. By maintaining closer alignment with benchmarks, managers can potentially improve risk-adjusted returns and enhance the attractiveness of their funds to risk-averse investors. However, they would need to do so at lower fees to remain competitive.

However, Cremers and Petajisto (2009) found that only when active management was executed effectively could it yield higher returns. Specifically, the Sharpe ratio increased with active management primarily within the top most active funds. This improvement in performance was primarily driven by the measure of active management called active share, rather than tracking error. This implies that active bets and stock selection, rather than frequent trading, generated the highest returns.

These findings shed light on two new perspectives: (1) nowhere does this study differentiate its findings between different degrees of active management, limiting the result. Similarly, Cuthbertson et al. (2010) found only the top 0-5% performers experiencing non-zero alpha, indicating that differentiating between different levels of sharpe ratio could similarly affect results. (2) tracking error only goes so far in estimating active management within mutual funds.

The results also contradict previous research conducted. Avramov and Wermers, as well as Chen et al., found that managerial skills and stock selection within US mutual funds resulted in higher returns. Fama and French found evidence of both under- and overperformance among mutual funds, with an overall indication of little to no true alpha. Cremers and Petajisto introduced the concept of active share, finding that funds with higher active shares tend to outperform their benchmarks due to effective stock selection. Cuthbertson et al. also found that a minority of top-performing funds exhibited non-zero alpha.

While the research area of asset management and mutual funds is well-explored, research specifically focused on the Swedish market is lacking, underscoring the need for additional studies.

6.2.2 Could the market landscape be changing the trajectory?

The rise of passive investment strategies is deeply rooted in the efficient market hypothesis (EMH) proposed by Eugene Fama (1970), which asserts that asset prices reflect all available information.

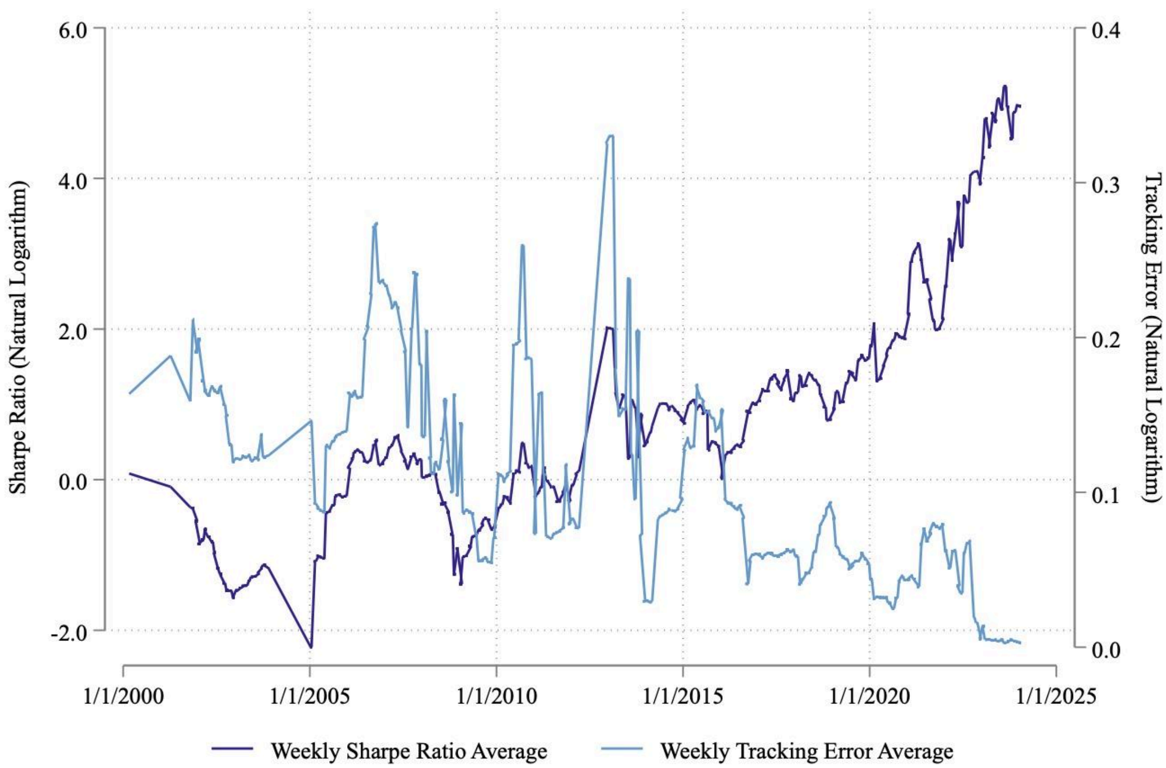
However, recent studies by Haddad, Huebner, and Loualiche (2022) have highlighted how the rise of passive investment impacts market dynamics, making demand curves for individual stocks more inelastic. More specifically, they found that passive investment might have caused aggregate demand curves for individual stocks to become roughly 15% more inelastic during the last 20 years. In their study, they investigated the competitive behavior of investors and tested the market theory that investors react to the behavior of other investors in the market. This idea suggests that as less aggressive traders surround an investor, she trades more aggressively, or the behavior of investor one is counteracted by investor two. Their study showed that these strategic reactions are far less impactful than the consensus view due to the increase in passive investment.

Passive investors have a “demand elasticity” of zero - their trading behavior does not depend on price changes but rather on the weight of an asset in the benchmark index. The increase in passive investment is, therefore, weighing down demand elasticity in the overall market.

While passively traded funds stem from the efficient market hypothesis and the thesis that the market incorporates all available information, meaning there should be no “beating the market”, this idea implies that their existence makes the market less efficient. Since passive money does not directly pay attention to all information out there, and passive investment vehicles are increasingly dominant, we end up with less accurate prices and a more volatile market. This is one plausible explanation for the flawed performance of actively managed funds.

Figure 6.2.2 shows that after 2013, there is a clear and persistent negative correlation between tracking error and the Sharpe ratio. Prior to this period, the relationship between these two metrics was more variable, with periods where higher tracking errors were sometimes associated with better risk-adjusted returns, particularly during the financial crisis of 2008-2009.

Figure 6.2.2. Sharpe Ratio and Tracking error over time



Post-2013, funds with higher tracking errors consistently exhibit lower Sharpe ratios. This indicates that more significant deviations from the benchmark index lead to poorer risk-adjusted performance. The consistent pattern suggests a structural change in the market or in the behavior of actively managed funds, making high tracking errors less effective as a strategy. This could be attributed to what Haddad, Huebner, and Loualiche (2022) argue, namely that the market may become less efficient as passive investment increases.

6.4 Limitations

6.4.1 Interpretation of Sharpe ratio

One limitation of this paper is that the study's results, based on the Sharpe ratio, do not allow for a clear distinction between the effects of volatility and actual returns (Elton et al., 1993). The Sharpe ratio captures both elements—excess returns and the volatility of those returns. As such, it is unclear whether the observed relationship between tracking error and the Sharpe ratio is primarily driven by fluctuations in returns (volatility) or the actual return levels. Future research should consider methodologies that can separately analyze these components to better understand what drives fund performance. This distinction is crucial for investors who need to understand whether poor Sharpe ratios are due to inherently volatile investment strategies or fund managers' lack of stock-picking skills. For example, Fama and French (2010) stated that the Sharpe ratio often fails to separate skill from luck, as it does not account for the role of random chance in fund returns.

Moreover, there is a potential for endogeneity in the relationship between tracking error and the Sharpe ratio. Poor fund performance might prompt fund managers to alter their investment strategies, leading to higher tracking errors (Elton et al., 1993; Carhart, 1997; Malkiel, 1995; Fama & French, 2010). In this case, the Sharpe ratio (performance) could impact the tracking error, suggesting a reverse causality. While this study controlled for several factors, including macroeconomic conditions and fund-specific characteristics, future research should further explore this potential endogeneity to better understand the dynamics between fund performance and tracking error.

By acknowledging these limitations, the study not only underscores the need for a cautious interpretation of the results but also highlights areas for further investigation to provide a more nuanced understanding of the performance dynamics of Swedish mutual funds. This caution is particularly important given the potential impact of the Sharpe ratio and endogeneity on the study's findings.

6.4.2 Suvivorship bias

One critical limitation of this study is the potential for survivorship bias. Survivorship bias occurs when the analysis includes only mutual funds that have survived until the end of the study period while excluding those merged or liquidated due to poor performance. This type of exclusion can lead to a skewed perception of the entire sample and an overestimation of the performance of the surviving funds, as the poorly performing funds are not represented in the dataset.

This study's data was sourced from NAV-center, which provided near-complete information on all Swedish actively managed mutual funds. However, it is likely that some funds that were closed or merged during the study period were not included in the dataset. This omission could result in an inflated average performance of the included funds and an underestimated level of risk associated with active management.

While previous studies have underscored the importance of this bias, emphasizing the necessity to adjust for survivorship bias in performance studies to avoid misleading conclusions (Brown et al., 1992; Malkiel, 1995; Elton et al., 1996; Carhart, 1997), some have found contradicting results. For example, studies conducted by Grinblatt and Titman (1994) and Ferson and Schadt (1996) suggest that the effect might be less dramatic than it was. Grinblatt and Titman (1994) found only an estimated yearly survivorship bias of 0.5%, with no significant effect on the overall results.

No studies have been conducted on survivorship bias in Sweden, resulting in a lack of academic insight into this particular issue within the Swedish market.

6.5 Future research

While this study provides insights into the performance of Swedish mutual funds and the relationship between tracking error and the Sharpe ratio, significant opportunities for further research remain.

Firstly, further studies that track the performance of Swedish mutual funds over extended periods can provide a deeper understanding of the overall effectiveness of active investment in Sweden. Such studies would offer valuable insights to both investors and fund managers, enhancing their ability to make informed decisions. Additionally, expanding the analysis to examine how different economic periods affect the relationship between tracking error and performance could yield further insights into how Swedish funds can better navigate economic cycles.

Secondly, a fundamental area for future research is the inclusion of comprehensive datasets that cover the entire lifecycle of all mutual funds, including those that have been closed or merged. This approach will mitigate the impact of survivorship bias, which often leads to an overestimation of performance by excluding underperforming funds. Addressing survivorship bias is particularly crucial in studies focused on the Swedish market, since none currently exist. By incorporating data on all funds initially present in the market, researchers can offer a more accurate and holistic assessment of mutual fund performance and associated risks.

Overall, focused studies on the Swedish mutual fund market will not only enhance academic knowledge but also provide practical insights for fund managers, investors, and policymakers in Sweden. Addressing these research areas can significantly contribute to our understanding of the dynamics of active management and its effectiveness in various economic contexts.

7. Conclusion

This study provides an in-depth analysis of the performance of Swedish mutual funds, particularly focusing on the relationship between tracking error and the Sharpe ratio. The findings indicate that higher tracking error, a measure of active management, is consistently associated with lower risk-adjusted returns. This suggests that active management strategies may not deliver the superior performance necessary to justify their higher fees, challenging the traditional notion that skilled managers can consistently outperform passive investment strategies.

The results align with the Efficient Market Hypothesis (EMH) proposed by Fama (1970), which posits that markets are generally efficient and that it is difficult for active managers to consistently beat the market. However, this study's findings contradict research by Cremers and Petajisto (2009), which suggested that funds with higher active shares tend to outperform due to effective stock selection. In the context of the Swedish mutual fund market, the benefits of active management appear to be limited.

The study also highlights the potential impact of survivorship bias, which could lead to an overestimation of mutual fund performance by excluding poorly performing funds that were closed or merged. This underscores the importance of considering survivorship bias in performance evaluations to avoid misleading conclusions.

Furthermore, the analysis suggests that the rise of passive investment may contribute to market inefficiencies, as posited by Haddad, Huebner, and Loualiche (2022). As passive investment increases, the market may become less efficient, complicating the efforts of active managers to identify and exploit mispriced securities.

In light of these findings, investors might reconsider the value proposition of actively managed funds and instead favor passive investment strategies with lower fees. For fund managers, there is an implication to prioritize risk management strategies that minimize deviations from benchmark indices to improve risk-adjusted returns and attract risk-averse investors, albeit at lower fees.

References

Avramov, D. & Wermers, R. (2006). Investing in Mutual Funds When Returns Are Predictable☆, *Journal of Financial Economics*, vol. 81, no. 2, pp.339–377

BlackRock. (2017). Index Investing Supports Vibrant Capital Markets, Viewpoint, Available online: https://www.blackrock.com/corporate/literature/whitepaper/viewpoint-index-investing-supports-vibrant-capital-markets-oct-2017.pdf [Accessed 2 April 2024]

Brinson, G. P., Hood, L. R. & Beebower, G. L. (1986). Determinants of Portfolio Performance, *Financial Analysts Journal*, vol. 42, no. 4, pp.39–44

Brown, S. J., Goetzmann, W., Ibbotson, R. G. & Ross, S. A. (1992). Survivorship Bias in Performance Studies, *Review of Financial Studies*, vol. 5, no. 4, pp.553–580

Chen, H.-L., Jegadeesh, N. & Wermers, R. (2000). The Value of Active Mutual Fund Management: An Examination of the Stockholdings and Trades of Fund Managers, *The Journal of Financial and Quantitative Analysis*, vol. 35, no. 3, p.343

Cochrane, J. H. (2001). Asset Pricing (Revised Edition), Princeton, USA: Princeton Univiversity Press

Cremers, K. J. M. & Petajisto, A. (2009). How Active Is Your Fund Manager? A New Measure That Predicts Performance, *Review of Financial Studies*, vol. 22, no. 9, pp.3329–3365

Cuthbertson, K., Nitzsche, D. & O'Sullivan, N. (2010). Mutual Fund Performance: Measurement and Evidence [1], *Financial Markets, Institutions & Instruments*, vol. 19, no. 2, pp.95–187

Daniel, K., Grinblatt, M., Titman, S. & Wermers, R. (1997). Measuring Mutual Fund Performance with Characteristic‐Based Benchmarks, *The Journal of Finance*, vol. 52, no. 3, pp.1035–1058

Durbin, J. & Watson, G. S. (1950). Testing for Serial Correlation in Least Squares Regression: I, *Biometrika*, vol. 37, no. 3/4, p.409

Durbin, J. & Watson, G. S. (1951). Testing for Serial Correlation in Least Squares Regression. II, *Biometrika*, vol. 38, no. 1/2, p.159

Elton, E. J., Gruber, M. J. & Blake, C. R. (1996). Survivor Bias and Mutual Fund Performance, *Review of Financial Studies*, vol. 9, no. 4, pp.1097–1120

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work, *The Journal of Finance*, vol. 25, no. 2, p.383

Fama, E. F. (1972). COMPONENTS OF INVESTMENT PERFORMANCE*, *The Journal of Finance*, vol. 27, no. 3, pp.551–567

Fama, E. F. & French, K. R. (2010). Luck versus Skill in the Cross‐Section of Mutual Fund Returns, *The Journal of Finance*, vol. 65, no. 5, pp.1915–1947

Ferson, W. E. & Schadt, R. W. (1996). Measuring Fund Strategy and Performance in Changing Economic Conditions, *The Journal of Finance*, vol. 51, no. 2, pp.425–461

Grinblatt, M. & Titman, S. (1994). A Study of Monthly Mutual Fund Returns and Performance Evaluation Techniques, *The Journal of Financial and Quantitative Analysis*, vol. 29, no. 3, p.419

Grinold, R. C. & Kahn, R. N. (1999). Active Portfolio Management: A Quantitative Approach for Producing Superior Returns and Selecting Superior Returns and Controlling Risk, McGraw-Hill Library of Investment and Finance

Grossman, S. & Stiglitz, J. (1980). On The Impossibility of Informationally Efficient Markets, *American Economic Review*, vol. 70, pp.393–408

Haddad, V., Huebner, P. & Loualiche, E. (2021). How Competitive Is the Stock Market? Theory, Evidence from Portfolios, and Implications for the Rise of Passive Investing, *SSRN Electronic Journal*, [e-journal], Available Online: https://www.ssrn.com/abstract=3821263 [Accessed 19 May 2024]

Hendricks, D., Patel, J. & Zeckhauser, R. (1993). Hot Hands in Mutual Funds: Short-Run Persistence of Relative Performance 1974-1988, *The Journal of Finance*, vol. 48, no. 1, pp.93–130

Ingersoll, J. E. (1987). Theory of Financial Decision Making, 3. [print.]., Savage, Md: Rowman & Littlefield

Jensen, M. C. (1968). THE PERFORMANCE OF MUTUAL FUNDS IN THE PERIOD 1945–1964, *The Journal of Finance*, vol. 23, no. 2, pp.389–416

Kosowski, R. (2011). Do Mutual Funds Perform When It Matters Most to Investors? US Mutual Fund Performance and Risk in Recessions and Expansions, *Quarterly Journal of Finance*, vol. 01, no. 03, pp.607–664

MacKinley, A. C. (1997). Event Studies in Economics and Finance, *Journal of Economic Literature*, vol. XXXV, pp.13–39

Malkiel, B. G. (1995). Returns from Investing in Equity Mutual Funds 1971 to 1991, *The Journal of Finance*, vol. 50, no. 2, pp.549–572

Malkiel, B. G. (2003). "The Efficient Market Hypothesis and Its Critics." *Journal of Economic Perspectives*, 17(1), 59-82.

Markowitz, H. (1952). Portfolio Selection, *The Journal of Finance*, vol. 7, no. 1, p.77

Sharpe, W. F. (1966). Mutual Fund Performance, *The Journal of Business*, vol. 39, no. S1, p.119

Treynor, J. (1965). How to Rate Management of Investment Funds, *Harvard Business Review*, vol. 43, no. 1, pp.63–75

Wooldridge, J. M. (2010). Econometric Analysis of Cross Section and Panel Data, The MIT Press

Data

Bloomberg

Fondbolagens Förening's NAV-centre

World Bank Indicators. (n.d.). GDP growth (annual %) - Sweden, Available online: GDP growth (annual %) - Sweden | Data (worldbank.org) [Accessed 1 April 2024]

Appendix

Table A3.1. All included funds.

Fund
AMF Aktiefond Småbolag
AMF Aktiefond Sverige
AktieAnsvar Sverige A
Aktiespararna Direktavkastning A
Aktiespararna Småbolag Edge
Aktiespararna Topp Sverige Hållbar A
Alfred Berg Sverige Gambak A
AstraZeneca Allemansfond
Avanza Småbolag by Skoglund
C WorldWide Sweden 1A
Carnegie All Cap A
Carnegie Micro Cap
Carnegie Småbolagsfond A
Carnegie SpinOff A
Carnegie Sverigefond A
Cicero Sverige A
Cliens Micro Cap A
Cliens Small & Micro Cap A
Cliens Småbolag A
Cliens Sverige B
Cliens Sverige Fokus A
Consensus Sverige Select A
Danske Invest Sverige Beta SA
Danske Invest Sverige Småbolag SA SEK
Didner & Gerge Aktiefond
Didner & Gerge Småbolag
Enter Micro Cap A
PriorNilsson Sverige Aktiv A
Ruth Core Nordic Small Cap
Ruth Core Swedish Equities
SEB Stiftelsefond Sverige A utd
SEB Sverige Expanderad
SEB Sverige Indexnära A
SEB Sverigefond
SEB Sverigefond Småbolag
SEB Sverigefond Småbolag C/R
SEB Sweden Equity C (SEK)
SEB Swedish Value Fund
Sensor Sverige Focus A
Simplicity Småbolag Sverige A
Skandia Cancerfonden
Skandia Idéer För Livet
Skandia Småbolag Sverige
Skandia Sverige
Skandia Sverige Exponering
Spiltan Aktiefond Småland
Spiltan Aktiefond Stabil
Spiltan Småbolagsfond
Storebrand Sverige A SEK
Storebrand Sverige Plus A SEK
Swedbank Robur Access Edge Sweden A
Swedbank Robur Access Sverige A
Swedbank Robur Exportfond A
Swedbank Robur Förbundsfond Sverige Plus

Enter Select A

Enter Småbolagsfond A

Enter Sverige A

Enter Sverige Hållbar Tillväxt A

Ethos Aktiefond A Utdelande

Evli Sverige Småbolag B

Finserve Micro Cap A

Folksam LO Sverige

Folksam LO Västfonden

Handelsbanken Sverige 100 Ind Cri A1 SEK

Handelsbanken Sverige Selektiv (B1 SEK)

Handelsbanken Sverige Tema (A1 SEK)

Highlight Sverige A

Humle Småbolagsfond A

Humle Sverigefond

Indecap Guide Q30 A

Indecap Guide Sverige A

Indecap Guide Sverige Offensiv C

Kvartil Investmentbolag+ Calculus A

Lannebo Småbolag

Lannebo Sverige

Lannebo Sverige Plus

Länsförsäkringar Sverige Vision A

Nordea Alfa

Nordea Inst Aktief Sverige ickeutd

Nordea Swedish Ideas Equity

Norron Active RC SEK

ODIN Sverige C SEK

Swedbank Robur Småbolagsfond Sverige A

Swedbank Robur Sverige A

XACT Svenska Småbolag

Öhman Marknad Sverige A

Öhman Marknad Sverige Bred A

Öhman Småbolagsfond A

Öhman Sverige Fokus D

Öhman Sweden Micro Cap A

Ruth Core Swedish Equities

SEB Stiftelsefond Sverige A utd

SEB Sverige Expanderad

SEB Sverige Indexnära A

SEB Sverigefond

SEB Sverigefond Småbolag

SEB Sverigefond Småbolag C/R

SEB Sweden Equity C (SEK)

SEB Swedish Value Fund

Sensor Sverige Focus A