Vaasan yliopisto
UNIVERSITY OF VAASA

Joona Perasto

Active Management and fund performance in the Nordic markets: Evidence from recent crisis periods

School of Accounting and Finance
Master’s thesis in Finance
Master’s Degree Programme in Finance

Vaasa 2026

UNIVERSITY OF VAASA
School of Accounting and Finance

Author:	Joona Perasto
Title of the thesis:	Active Management and fund performance in the Nordic markets: Evidence from recent crisis periods
Degree:	Master of Science in Economics and Business Administration
Degree Programme:	Master's Degree Programme in Finance
Supervisor:	Timo Rothovius
Year:	2026 **Pages:** 83

ABSTRACT:

This thesis examines the performance of actively managed equity funds in the Nordic stock markets between 2017 and 2024. The main objective of the study is to investigate whether true active management, measured by Active Share, provides investors with downside protection during market crises consistent with Glode's (2011) insurance hypothesis. The dataset consists of Nordic equity funds. The empirical analysis is conducted using a fixed-effects panel data model. The study employs the Carhart four factor model to control systematic risk-factors (Size, value and momentum).

In normal market conditions, high Active Share funds do not on average generate statistically significant risk-adjusted excess returns. During a sudden fear and liquidity shock, such as the COVID-19 crisis in the spring of 2020, high Active Share provided protection. Although the funds suffered absolute losses due to their small-cap tilt, truly active managers were able to generate significant risk-adjusted alpha. In contrast, during the 2022 crisis, active management did not offer similar protection, and stock picking failed to mitigate the market shock. The study provides evidence of a shift in manager behavior: during the COVID-19 panic, there was a tendency among managers to reduce active risk by moving closer to their benchmark indices

KEYWORDS: Active Share, Tracking Error, Mutual funds, Active Management, Insurance hypothesis, Carhart four-factor model, Nordic equity markets, COVID-19 Pandemic, Market shocks

VAASAN YLIOPISTO
School of Accounting and Finance
Tekijä: Joona Perasto
Tutkielman nimi: Active Management and fund performance in the Nordic markets: Evidence from recent crisis periods
Tutkinto: Kauppatieteiden maisteri
Opintosuunta: Rahoituksen maisteriohjelma
Työn ohjaaja: Timo Rothovius
Valmistumisvuosi: 2026 **Sivumäärä:** 83

TIIVISTELMÄ:
Tämä tutkielma tarkastelee aktiivisesti hoidettujen osakerahastojen suoriutumista pohjoismaisilla osakemarkkinoilla vuosina 2017-2024. Tutkimuksen pääasiallinen tavoite on selvittää tarjoaako, aito aktiivinen salkunhoito, mitattuna Active Sharella sijoittajille suojaa markkinakriisien aikana Gloden (2011) vakuutushypoteesin mukaisesti. Aineisto koostuu pohjoismaisista osakerahastoista ja empiirinen analyysi toteutetaan kiinteiden vaikutusten paneelidatamallilla (fixed effects). Systemaattisten riskitekijöiden, kuten koon, arvon ja momentumin kontrolloimiseksi tutkimuksessa hyödynnetään Carhartin nelifaktorimallia. Tutkimustulokset osoittavat että normaaleissa markkinaolosuhteissa korkean Active Share –luvun rahastot eivät keskimäärin tuota tilastollisesti merkittävää riskikorjattua ylituottoa kulujen ja riskifaktorien huomioimisen jälkeen. Äkillisen pelko- ja likviditeettishokin , kuten kevään 2020 koronakriisin aikana aito osakepoiminta kuitenkin toimi tehokkaana suojana. Vaikka rahastot kärsivät absoluuttisia tappioita pienyhtiöpainotuksensa vuoksi, aidot aktiiviset salkunhoitajat kykenivät tuottamaan merkittävää riskikorjattua alphaa. Sen sijaan vuoden 2022 kriisin aikana aktiivinen salkunhoito ei tarjonnut vastaavaa suojaa, eikä osakepoiminta kyennyt lieventämään markkinashokkia. Lisäksi tutkimus antaa viitteitä salkunhoitajien käyttäytymisen muutoksesta: koronapaniikin aikana oli havaittavissa suuntaus, jossa aktiivista riskiä pyrittiin mahdollisesti alentamaan hakeutumalla lähemmäs vertailuindeksiä.

AVAINSANAT: Active Share, Tracking Error, osakerahastot, aktiivinen salkunhoito, vakuutushypoteesi, Carhartin nelifaktorimalli, pohjoismaiset osakemarkkinat, COVID-19-pandemia, markkinashokit

Contents

Abbreviations

EMH= Efficient market hypothesis
AMH= Adaptive market hypothesis

Research tools

Bloomberg and Refinitiv Data stream. While the content is original, AI tools were used for proofreading and stylistic adjustments.

1 Introduction

The mutual fund industry has significantly shifted over the past two decades from active to passive strategies (Anadu et al., 2020). The shift towards passive investing is driven by the cost advantage of index funds, as demonstrated by Sharpe's (1991) arithmetic of Active Management. Active Management generally underperforms passive strategies net of fees (Fama & French, 2010). However, Active Management still has its own role in the financial markets. According to Grossman and Stiglitz (1980) Active Management is an important mechanism to keep markets efficient by correcting mispricing. Glode (2011) extends this rationale by arguing that the value of activeness is state-dependent. He proposes that active managers justify their fees by exploiting mispricing during market downturns, acting as insurance for investors when marginal utility is highest.

Before 2009, Active Management was measured by tracking error. It measures how accurately a fund's return mimics the returns of the benchmark index. However, this measure has a fundamental problem. The measure effectively spots factor bets (e.g., overweighting specific industries or sectors) but fails to distinguish stock selection. A fund manager can build a portfolio that mimics index holdings very closely, keeping tracking error low, while charging active fees. This practice, which tracking error fails to detect, is known as closet indexing. Cremers and Petajisto (2009) introduced a new measure for Active Management called Active Share. Authors argue that high Active Share is a prerequisite for outperformance. Closet indexers are expected to underperform the benchmark net of fees. Beyond the academic debate, closet indexing has emerged as a regulatory concern. The European Securities and Markets Authority (ESMA, 2020) identified closet indexing not purely as a performance issue but as a failure in investor protection. Flam and Vestman (2017) highlight the severity of this problem, finding the average Active Share for Swedish equity funds to be as low as 0.36. Therefore, it is possible that prior evidence against active management is misleading, as those studies may have failed to distinguish between high-conviction managers and closet indexers.

Following the seminal work by Cremers and Petajisto (2009), multiple studies have supported the predictive power of Active Share. Petajisto (2013) extended the original dataset through the 2008 financial crisis and confirmed that high Active Share funds generate significant abnormal returns, suggesting that the anomaly is robust even during crises. Cremers et al. (2016) provided international evidence across 32 countries, finding that high Active Share predicts outperformance globally, including the Nordic region

The Active Share metric has faced academic critique. Frazzini et al. (2016) argue that the reported outperformance of high Active Share funds is not driven by stock-picking skill, but rather by a systematic exposure to small-cap stocks. To address this critique, this study uses the Carhart (1997) four-factor model, which controls for the size (SMB) factor, market, value, and momentum effects.

Evidence regarding performance of active management during extreme market stress remains divided. While the insurance hypothesis (Glode, 2011) suggests active managers add value during downturns, Pástor and Vorsatz (2021) find that active funds generally underperformed during the COVID-19 crash. Their study did not differentiate between stock-pickers and closet indexers. While Flam and Vestman (2017) found a weak relationship between Active Share and returns in Sweden from 1993 to 2013, they did not isolate the impact of the crisis using specific shock periods. This leaves a significant gap in Nordic literature regarding the state-dependent nature of Active Share. This thesis addresses these gaps by isolating the COVID-19 crash and the 2022 geopolitical crisis to test whether active management provides value during market crises.

1.1 Purpose of the study

The purpose of this study is to examine active portfolio management during two distinct crisis environments in the Nordic financial markets: the 2020 COVID-19 volatility shock and the 2022 geopolitical and inflationary crisis following Russia's invasion of Ukraine. The rationale for selecting Nordic stock markets is that they provide heterogeneous empirical material within a shared institutional framework (Andersen et al., 2007; Thomsen, 2016). Nordic markets provide a well-diversified risk profile, being heavily weighted towards the industrials, financial and health care sectors (MSCI, 2026).

These crises are interesting because they represent two opposite market environments: The sudden COVID-19 crash and the long-lasting inflationary and energy crisis following the 2022 invasion of Ukraine.

Methodologically, to capture the dynamic and state-dependent nature of managerial skill, the empirical analysis incorporates specific crisis dummy variables to isolate the immediate COVID-19 crash (Spring 2020) and the prolonged 2022 geopolitical crisis. The study seeks to answer the following research question: *Did high Active Share provide economic value and downside protection in the Nordic equity markets during the COVID-19 crash and the 2022 geopolitical crisis?* To address this research question, the empirical analysis tests the following hypotheses. First, to establish a baseline for fund performance, the general value proposition of Active Management is evaluated over the full sample period:

H1: High Active Share funds generate positive net alpha.

Moving beyond the baseline performance, the study examines the state-dependent nature of managerial skill during market shocks. The COVID-19 pandemic and the 2022 geopolitical crisis created fundamentally different market conditions. The former was a sudden shock driven by a fear and liquidity constraints while the latter triggered a prolonged inflationary regime shift. Because of these contrasting environments, this study tests the protective value of Active management separately for each crisis with the following hypotheses:

H2A: Active Share is positively associated with net alpha during the COVID-19 crash.
H2B: Active Share is positively associated with net alpha during the 2022 geopolitical crisis.

Previous literature suggests that market uncertainty affects managerial behaviour. Framework by Petajisto (2013) suggests that fund managers may reduce their activeness during a crisis to minimize career risk when market uncertainty rises. Therefore, the hypothesis 3 is as follows:

H3: ***Average Active Share decreases during crisis periods.***

If managers seek to reduce active risk and career risk during times of high uncertainty, they are likely to move their portfolios closer to benchmark indices. This shift would indicate that investors are left paying high active fees for a passive portfolio management, potentially losing the downside protection they expect during market shocks.

While Active Share has been widely researched in U.S. markets (Cremers & Petajisto, 2009; Petajisto, 2013), there is a significant gap in the literature regarding its effectiveness in small open economies during extreme geopolitical stress. More specifically, empirical evidence is lacking on whether Active Management provided “insurance value” as proposed by Glode (2011), during the recent Nordic market shocks. By contrasting a deflationary liquidity shock with an inflationary macro crisis, this study aims to fill this gap and challenge the universality of the insurance hypothesis.

1.2 Structure of the thesis

The rest of this thesis is structured as follows. Chapter 2 reviews the theoretical framework of portfolio management. Chapter 3 presents a literature review of active portfolio management. Chapter 4 introduces the data and methodology, and Chapter 5 presents the empirical findings. Lastly, chapter 6 discusses the limitations of the study and Chapter 7 concludes.

2 Theoretical framework

To build a foundation for the empirical analysis, this chapter reviews the essential theoretical framework. The chapter begins by discussing portfolio management before moving to the measurement of the Active Management.

2.1 Portfolio Management

The debate in portfolio management centers on the choice between passive and active strategies. These two views rely on conflicting theoretical views regarding market efficiency and diversification. Usually, Active Management is associated with higher fees. The rationale behind higher fees is the manager's salary and transaction fees that rise simultaneously with higher activeness. From an investor's perspective, Active Management is a rational investment decision if fund managers can gain excess returns that cover higher fees. Excess returns are unusual and most of the active funds lose to the index net of fees during normal times. Managers must have exceptional skills to exceed the returns of the benchmark index net of fees. However, this rationale might not be so straightforward during market distress. Markets may not always be rational during crises. Mechanisms such as stop-loss orders can trigger chain reactions leading to automated selling. When stock markets decline sharply, it can lead to inefficiencies in pricing. This environment can be an opportunity for a skilful manager to exploit. The next chapters will cover these basic concepts of portfolio management.

2.1.1 Active Management

Active Management is a style of portfolio management strategy where fund managers make many investment decisions with the goal of outperforming the benchmark index. (Fuller et al., 2010, p. 35). Active funds have some advantages that explain their demand. Gruber (1996, pp. 784-785) listed these advantages. Active funds offer several advantages, such as customer service, record keeping and relatively low transaction costs. However, professional management remains the primary distinguishing factor. Also, he explained the demand for active funds through pricing mechanisms (p. 785). The author stated open-end mutual funds sell at net asset value; therefore, the skill of management cannot be fully priced in. For instance, funds with inferior managers are priced similarly to funds with superior managers by net asset value. He argued that future performance could be only partially predicted based on past performance because these funds are sold at NAV, the market value of the assets owned. Sophisticated investors could use this acknowledgment to their benefit and gain positive risk-adjusted returns on new cash flows exceeding both the average active fund and passive fund (p. 807). Gruber (1996, p. 807) explained that weak funds survive because the disadvantaged clients keep money in inferior funds.

The existence of Active Management can be justified theoretically by the paradox presented by Grossman and Stiglitz in 1980. They (p. 393) described a fundamental problem concerning market efficiency. Authors argue that perfectly informationally efficient markets are impossible when information is costly. Grossman and Stiglitz (1980, p. 393) describe this fundamental problem as follows: “If competitive equilibrium is defined as a situation in which prices are such that all arbitrage profits are eliminated, is it possible that a competitive economy can always be in equilibrium? Clearly not, for then those who arbitrage make no (private) return from their (privately) costly activity.” Consequently, if the prices reflected all available information, no investor would have an incentive to use resources to analyse markets and assets. To resolve this problem, they propose an equilibrium degree of disequilibrium where prices only partially reflect available information (p. 393). This is a rationale for Active Management as expenses related to getting information could be covered. By actively using resources for information gathering and analysis, fund managers will reduce inefficiencies in markets and therefore contribute to efficient markets.

Historically, fees of Active Management have not been constant. Ellis (2014, p. 16) notes that fees rose significantly in the 1970s and 1980s through technology and competition. This is consistent with Grossman and Stiglitz’s views: more efficient markets made getting an information advantage harder and more expensive and therefore higher fees were justified.

2.1.2 Passive management

Passive management is a portfolio strategy where trading activity is minimized to reduce transaction costs and taxes. A popular method is to mimic the performance of an externally specified index (Fuller et al., 2010, p. 35). However, the line between passive and active investing is blurred. For instance, an investor investing in the OMX25 index makes an active decision. Firstly, the investor made an active bet on the Finnish market and secondly, they decided to invest in large-cap equities. Therefore, passive investing can be viewed as an active decision.

The theoretical justification for passive investing was articulated by William Sharpe in 1991. In his paper (p. 1), he notes that the relationship between active and passive management can be governed by two fundamental arithmetic theories and facts:

1. Before costs, the return on the average actively managed dollar must equal the return on the average passively managed dollar.
2. After costs, the return on the average actively managed dollar must be lower than the return on the average passively managed dollar.

Since passive investors hold positions that represent the whole market, they earn exactly the market return before fees. Consequently, active investors must also earn market return before fees in aggregate. Because Active Management has significantly higher costs compared to passive strategies, the zero-sum game of gross returns becomes a negative-sum game for active investors after fees are deducted. This arithmetic reality is that for an active manager to be successful, they must possess' skill to not only beat the market but also overcome significant costs related to their strategy.

2.1.3 Modern portfolio theory

Modern portfolio theory was developed by Markowitz (1952). It is a model for optimization of a portfolio for large private investors or institutional investors that aims to create a balanced portfolio with maximized risk-adjusted returns. The theory is based on the thought that risk can be reduced but can’t be perfectly eliminated, as securities can be highly correlated but not perfectly. Markowitz argues that portfolios with securities that are highly correlated should be avoided as they hinder effective risk diversification. Investors should seek securities that have low or negative correlation. The core insight of this theory is that a portfolio’s overall risk is not simply the average of individual assets' risk but is covariances between assets. The core of the theory is to create a portfolio on the efficient frontier, which represents a set of portfolios that offers the highest expected return for the given risk and that consists of risky assets. Rational investors should always select a portfolio on this frontier.

While Markowitz's (1952) modern portfolio theory created a mathematical foundation for diversification by introducing the efficient frontier, it did not identify a single universally optimal portfolio of risky assets. Tobin (1958) expanded Markowitz’s work by introducing the risk-free asset, leading to the separation theorem, which states that the investment decision involves two separate steps: first, identifying the optimal portfolio of risky assets and second, deciding how to allocate capital between this risky portfolio and the risk-free asset based on individual risk tolerance. Tobin argued that all investors should theoretically hold the same portfolio of risky assets, only differing in their leverage or cash holdings.

Tobin’s (1958) concept of a composite portfolio, formed with fixed proportions of risky assets, created a theoretical framework for what Sharpe (1964) would later formalize as the market portfolio. Sharpe (1964) also introduced the Capital Market Line (CML), which points to a new superior set of investment opportunities available. This theory simplifies the investor’s investment decision. Instead of creating a unique portfolio from countless individual assets, the decisions are reduced to a single allocation choice: how much capital to allocate to the risk-free assets versus this one optimal risky portfolio, later known as the market portfolio. This framework implies that risks can be divided into two components: systematic risk, also known as market risk or undiversifiable risk. It is the risk inherent in the whole market. The second component is unsystematic risk, which is asset-specific risk and can be fully eliminated by diversification.

Building on this foundation, the Capital Asset Pricing Model (CAPM) was introduced independently by Sharpe (1964), Lintner (1965) and Mossin (1966). Taking unsystematic risk is not rewarded by markets. The only relevant risk is systematic, undiversifiable risk measured. According to the theory, the market only rewards systematic risk. Firm-specific risk is unrewarded. The model is as follows:

$$E(R_i) = R_F + \beta_i E(R_M)$$

Where E(R_i) is the expected return, $R_F$is the risk-free rate and B_i measures sensitivity to the market by beta. From the perspective of modern portfolio theory, Active Management is hard to justify, as active strategies have unrewarded risk and higher cost without a guarantee of higher expected returns.

2.1.4 Efficient market hypothesis

Active portfolio management is theoretically meaningful only if markets are not perfectly efficient, because there should be no mispricing among any securities. The goal of Active Management is to generate excess returns, or alpha, by identifying and exploiting mispricing. As introduced by Fama (1970), the Efficient Market Hypothesis (EMH) posits that security prices fully reflect all available information. The efficient market hypothesis is essential to Active Management and to value added by having a fund manager making active decisions. By not having efficient markets per the efficient market hypothesis, there is theoretically still a place for active managers, at least measured by gross returns. If markets were to be effective, there would be no place for active managers because no investor could consistently earn excess returns on a risk-adjusted basis. Fama (1970) presented EMH in three forms based on available information: Weak, semi-strong and strong forms of efficiency.

According to the weak form of market efficiency, all past returns and price data are reflected in current pricing. Therefore, technical analysis is not a suitable tool for predicting future price movements in premises of weak form of market efficiency. In addition to past return and price data, the semi-strong form of market efficiency consists of all public information, such as financial statements and economic data. A strong form of efficiency consists of all information, including both public and private.

Despite its central role in finance, EMH has been constantly criticized. Thaler (1987, pp.197-199) criticizes the efficient market hypothesis by pointing out different behavioral anomalies such as the January effect, where returns are abnormally high in January. The fact that such anomalies continue to persist challenges the strict and traditional view that market efficiency is a constant state. Explanation for why these mispricings exists is "limits to arbitrage". Concept was introduced by Shleifer and Vishny in 1997. They argue that even if there are inefficiencies, managers ability to exploit them is constrained by fundamental risk, transaction costs and agency problems. To make sense of these different anomalies' academics needed another framework that treats market efficiency as a flexible and always changing state rather than a permanent state.

2.1.5 Adaptive market hypothesis

Andrew Lo (2004) presents the adaptive market hypothesis (AMH) as an alternative to EMH. Lo (pp. 17-18) argues that market efficiency is not a permanent characteristic of financial markets but rather a dynamic outcome of competition among different "species" of market participants. AMH argues that the degree of market efficiency is dependent on the context and fluctuates based on the number of participants and market conditions. This framework is especially relevant during crises, when normal market competition may weaken temporarily. In normal market conditions, competition ensures that profit opportunities are quickly exploited, maintaining high market efficiency. However, a sudden environmental shock, such as the 2022 geopolitical crisis, can disrupt this equilibrium. A crisis can lead many investors to panic or rely on outdated heuristics. In such situations, temporary mispricing may emerge as many investors react simultaneously to uncertainty. Fund managers can then exploit these temporary inefficiencies before the market adapts and competition returns to the markets.

While the adaptive market hypothesis provides a theoretical proof for the existence of profit opportunities during market downturns, empirically detecting such alpha requires a framework to control for known risk factors. To differentiate between true manager skill and exposure to market factors, researchers rely on factor models, e.g., the Carhart four-factor model.

2.1.6 Carhart four-factor model

Mark Carhart presented the 4-factor model in 1997. It is based on Fama and French's (1993) 3-factor model that includes market, size and value factors (p. 61). The 4-factor model adds Jegadeesh and Titman's (1993) momentum factor to the 3-factor model (p. 61). Carhart's (1997) evidence that return persistence is explained by factor exposure rather than managerial skill presents a challenge for the justification of Active Management.

Carhart utilized his four-factor model to study the hot hands phenomenon that was observed in earlier studies. He demonstrates that short-term excess returns are primarily driven by the momentum effect. However, he notes that individual funds do not earn consistently higher returns simply by following a momentum strategy. He finds that persistence of return is explained by investment expenses and common factors**.** The only significant exception he identifies is the strong and persistent underperformance of the worst-performing funds (p. 57). His findings suggest that most of what appears to be managerial alpha is passive exposure to well-known market factors. Carhart's (1997) four-factor variables are used in this study to control for these factors, ensuring that the observed performance is not rewarded for passive exposure to well-known market anomalies.

2.2 Active Management measurement

Measuring Active Management is essential to evaluate active managers' ability to add value net of fees. Simple return data alone does not tell if the fund is truly active rather than a closet indexer. Therefore, measures have been developed that are based on return deviations or fund composition differences from the benchmark index. In this chapter, these essential measures are reviewed along with their ability to spot real activity from closet indexing.

2.2.1 Tracking error

Tracking error, also known as tracking error volatility, is the traditional way to measure active management. It is commonly defined as the time-series standard deviation of the difference between a fund's return and its benchmark index return (Cremers & Petajisto, 2009). Typical active manager aims for an expected return higher than the benchmark index but simultaneously seeks to keep tracking error low to minimize the risk of significantly underperforming the index (Cremers & Petajisto, 2009). Tracking error for a fund is calculated as follows:

$$Tracking\ error = \sqrt{\frac{\sum_{i=1}^{N}(R_P - R_B)^2}{N-1}}$$

Where $R_P$is the return of the portfolio in period I, the R_B The return of the benchmark index in periods I and N represent the total number of observations in the time series.

Tracking error itself is not a clear measure of Active Management because it does not separate two different strategies: stock selection and factor timing (Cremers & Petajisto, 2009). This can happen if a fund manager is a "diversified stock picker" who actively selects stocks but keeps the industry weights like the benchmark.

On the other hand, a fund can have a high tracking error but a low Active Share. This is called factor timing, where the manager makes a bet on whole industries or sectors. Because the fund's returns will be volatile compared to the benchmark, tracking error could be high even if the stock holdings are like the index (Cremers & Petajisto, 2009). This shows that tracking error and Active Share measure different things. According to them, tracking error is a good proxy for factor bets. Authors also found that tracking error was not related to fund return, but the activeness captured by Active Share was.

2.2.2 Active Share

Cremers and Petajisto (2009) introduced a new measure for measuring the activeness of fund managers called Active Share. In addition to introducing new measures for Active Management, it also connects it to tracking error. Active Share compares the fund's composition to the index. It measures the percentage of portfolio holdings that differ from the benchmark index's holdings. It is calculated by the following formula:

$$Active\ share = \frac{1}{2}\sum_{i=i}^{n} | w_{fund,i} - w_{index,i} |$$

where $w_{fund,i}$is the weight of assets I in the fund's portfolio, $w_{index,i}$ is the weight of the assets i in the benchmark index and n represents the total number of assets. They categorized funds into three categories based on their Active Share: index funds, closet indexers and active. Index funds are funds with an Active Share lower than 20%, while closet indexers are funds with a relatively low Active Share of 20-60%. Active funds are funds with an Active Share higher than 60%. Intuitively, one could argue that a fund with an Active Share over 50% is active. However, authors argued that a fund with 50% Active Share cannot be considered as truly active. Their logic is that no more than half of all stocks can outperform the market average. Fund managers with more than 50% overlap are knowingly holding stocks they expect to underperform. Such a portfolio is not purely active but "hybrid," combining a large overlap with the index with a smaller number of active bets.

Table 1 Simplified calculation of Active Share

Stock	Index weight %	Fund weight %	Absolute difference	Impact on active share
Stock 1	40 %	25 %	15 %	8 %
Stock 2	10 %	35 %	25 %	13 %
Stock 3	35 %	0 %	35 %	18 %
Stock 4	15 %	40 %	25 %	13 %
Total	100 %	100 %	100 %	50 %

Table 1 provides a simplified visualization of the Active Share calculation for a hypothetical four-stock portfolio. The calculation process determines the absolute difference between the index weight and the fund weight for each holding. Summing these differences and dividing by two yields an Active Share of 50%, which represents the exact proportion of the fund's portfolio that deviates from the benchmark index. Cremers and Petajisto (2009, pp. 7-8) suggested that Active Share should be used with tracking error. While Active Share serves as an effective proxy for stock selection, tracking error is a more suitable proxy for factor timing. By using these measures simultaneously, investors can evaluate both dimensions of portfolio management.

2.3 Closet Indexing and Regulatory Implications

European regulatory bodies have framed closet indexing not purely as a performance issue but as structural conduct risk and failure in investor protection. The European Securities and Markets Authority has monitored this practice. Their findings emphasize that investors investing in closet indexers face lower expected net returns compared to active funds, as the marginally lower fees of closet indexers do not compensate for their reduced performance (ESMA, 2020)

In addition to ESMA’s initiative, national authorities have intensified their action regarding closet indexers. The Central Bank of Ireland conducted a review of UCITS funds, identifying problems in disclosure. Investors were not given sufficient or accurate information about the fund's investment strategy in the prospectus. Irish authorities require fund boards to continuously evaluate fee structures and ensure that prospectuses and key investor information documents accurately reflect the targeted level of outperformance and the actual use of benchmarks (Central Bank of Ireland, 2019).

The UK's Financial Conduct Authority (FCA) has recently taken a strict stance on this issue. They draw a clear line between closet trackers and funds where the manager makes active choices but quietly keeps the risk profile close to a benchmark. This lack of transparency misleads investors. The FCA introduced new rules aimed at creating a fair and transparent market where investors can easily understand the products they purchase, with penalties for non-compliant firms. The FCA’s interventions have led to financial consequences, including tens of millions of pounds paid to misled investors and substantial fines for non-compliant asset managers (Kjørven, 2018; FCA, 2018).

2.4 Characteristics of Nordic stock markets

To fully understand the dynamics of active portfolio management and the prevalence of closet indexing, it is important to examine in what kind of environments these funds operate. The Nordic markets have different structural features that differentiate them from larger markets such as the United States. This section defines features of the Nordic environment by dividing them into two categories: the real economy and regional financial markets.

2.4.1 Stock markets and institutional features

The Nordic ownership structure is characterized by concentrated ownership and large blockholders. These structures vary across countries, ranging from bank-based groups in Sweden to state ownership in Norway and foundation ownership in Denmark (Thomsen, 2016, pp. 196-197). While Thomsen (2016) highlights Sweden, Norway and Denmark, the concentrated ownership in Finland is largely driven by Finnish state pension funds and the state-owned investment companies (Airaksinen et al., 2014, p. 171).

2.4.2 The real economy: Export dependency and geopolitical risks

Nordic countries are small, open economies that are highly dependent on trade and exports (Andersen et al., 2007, p. 31). This openness makes the Nordic economy and financial markets sensitive to global macroeconomic shocks.

3 Empirical literature

Empirical literature on Active Management is divided. Early studies show that active managers, on average, fail to outperform markets net of fees. However, more recent studies using new metrics such as Active Share challenge this view by differentiating between closet indexers and truly active managers. The success of active strategies can depend on market circumstances and conditions, especially during crises or market downturns.

3.1 Active Management

Scepticism regarding active portfolio management is not a new phenomenon. In his study, Sharpe (1966, p. 138) observed that on a risk-adjusted basis, mutual fund managers failed to outperform the market on average; instead, they underperformed the benchmark net of fees. These findings were later consolidated by many academics. For instance, a seminal study using risk-adjusted measures was conducted by Jensen in 1968. He introduced a risk-adjusted measure called Jensen Alpha. In his study of 115 mutual funds between 1945 and 1964, he found that on average, funds earned 1.1% less per year after fees than the market index (p. 405). However, the most significant finding was that active managers could not beat the market even when measured by gross returns (p. 407). Jensen concluded that managers did not possess the forecasting ability to predict security prices well enough to add value to investors, net of fees. On the other hand, fund managers were able to minimize unsystematic risk by diversifying their portfolios effectively (p. 415). More recently, Fama and French (2010, p. 1915) argue that active investing must be a zero-sum game before costs. Utilizing bootstrap simulation to distinguish skill from luck, they found that few active funds produce benchmark-adjusted expected returns that cover their costs (p. 1915). Furthermore, while they found evidence of manager skill when examining gross-returns, the benefits for investors are small. Managers capture the benefits, leaving investors with net returns that generally underperform the market (pp. 1916, 1945).

This dynamic is theoretically explained by the rational model of active portfolio management presented by Berk and Green in 2004. They (p. 1271) explained that active managers do not outperform benchmarks because superior ability leads to increased fund flows. This complements Fama and French's (2010) findings. Investors rationally interpret past returns as evidence of manager skill, directing capital to successful funds (p. 1271). While managers will benefit in the form of bigger fees from fund flows, the increasing size leads to diseconomies of scale, driving net returns for investors down to the benchmark level (p. 1273). This dynamic can lead to a situation where the fund resembles more of an index. Increasing flows can lead to a situation where the active manager must invest in more liquid stocks instead of smaller, more illiquid stocks, causing the portfolio to increasingly resemble the index.

3.2 Active Share studies

While early empirical literature paints a pessimistic picture of Active Management, largely presenting it as a zero-sum game, these studies have limitations. They treat all funds labelled as active the same. This approach does not differentiate between managers that truly deviate from the benchmark and those that closely replicate the benchmark while charging active fees. The introduction of Active Share by Cremers and Petajisto (2009) resolved this problem by comparing the composition of the benchmark index to the fund’s portfolio. They used a method where they selected the best-fit benchmark from 19 different indexes and selected the index with the lowest Active Share (p. 12). This framework allows them to identify “closet indexers,” funds that claim to be active and charge active fees but replicate the index closely. Their main findings are that funds with the highest Active Share (over 80%) outperformed benchmarks by 1.51%-2.4% per year. After accounting for fees and transaction costs, outperformance decreased to 1.13%-1.15% yearly (p. 3). It can be interpreted that the stock-selection dimension of Active Management captured by Active Share is rewarded by markets. Authors conclude that the most active stock pickers possess the skill to outperform benchmarks even net of fees. In contrast, tracking error was found to be unrelated or negatively related to returns. This may indicate that factor portfolios may be too efficiently priced or too difficult for managers to predict correctly. Finally, closet indexers were found to exhibit zero skill, underperforming their benchmark by the amount of expenses (Petajisto and Cremers, 2009, pp. 3-4).

These findings shifted the academic debate initiated by Jensen (1968). While the arithmetic of the zero-sum game (Sharpe, 1991) dictates that the average active dollar must underperform the market after fees, Cremers and Petajisto (2009) demonstrate that the losers in this equation are mainly closet indexers and managers relying on factor bets. These groups underperform their benchmarks, effectively financing outperformance in high Active Share funds. This implies that while the average active fund may lose to the market net of fees, truly active managers can generate value at the expense of less skilled managers or managers that take factor bets and closet indexers.

3.2.1 Role of patience

Despite the increasing market efficiency, some researchers argue that Active Management can still succeed by shifting focus from information speed to investment horizon. Cremers and Pareek (2016) studied the turnover rate of funds. The main findings are that among high Active Share portfolios, funds with patient investment strategies with holding durations of over two on average outperform the market by over 2% per year (pp. 288, 304). Funds trading frequently underperform, including those with Active Share and therefore destroy value (p. 288). Low Active Share funds on average underperform even with patient strategies; patience alone is not sufficient for outperformance. (p. 288). These excess returns are explained by the fact that markets have a limited amount of arbitrage capital devoted to patient and active investment strategies (p. 288). The author states that active managers require investors to be patient. Such investor patience might be rare, as both fund managers and their investors may need to wait years before getting rewarded for their patience.

3.2.2 Resilience in Crisis

Petajistö (2013) expanded the study by Cremers and Petajisto (2009) to cover the 2008-2009 financial crisis. Instead of selecting a benchmark index with the best fit, they used the prospectus benchmark if available for the selected fund. Only if there is no prospectus benchmark available do they use the "best fit" approach (pp.8-9). This update was critical to determine whether the outperformance of high Active Share funds was a product of bull markets or if the effect persisted during the market crisis. Petajisto (2013, p.1) finds that performance remained consistent during the financial crisis. Closet indexers and funds focusing on factor bets lost their benchmark after fees. This implies that the value of active stock selection does not disappear during market crashes. Furthermore, the author found that closet indexing tends to increase in volatile and bear markets. This suggests that when uncertainty rises, managers tend to reduce their active risk to align closer with the benchmark. This is highly relevant for the study, as it indicates that the level of Active Management may decrease during crises, making the identification of truly active managers even more important.

3.2.3 International evidence and Nordics

While early Active Share studies focused on the U.S. markets, Cremers et al. (2016, p. 543) provided international evidence covering 32 countries, including the Nordics. The main finding is that (p. 556) Active Share as a predictor of future performance holds internationally and is consistent with Cremers and Petajisto's (2009) results in U.S. markets. Furthermore, they (p. 549) argue that the rise of low-cost index funds has forced active funds to lower their fees and become more distinctive by becoming more active. This validates the use of Active Share as a performance metric also in the Nordic context. There are significant differences in activity levels across Nordic countries (Cremers et al., 2016, Table 1). In their sample, Sweden was dominated by closet indexers, while in Norway and Denmark, the majority of funds were truly active. This heterogeneity provides an interesting sample to test Active Share.

Evidence from the Nordic region challenges the universality of the Active Share. Flam and Vestman (2017, p. 3, 5) conducted a study in their working paper on actively managed Swedish equity mutual funds from 1993 to 2013. They detected outperformance in the early part of the sample from 1993 to 2001; from 2002 to 2013, they detected negative net excess returns of -1.47%. The authors found no evidence of managers' stock-picking skills.

Existing literature presents a geographical divide. While U.S.-based studies suggest Active Share predicts outperformance, the leading Nordic study implies it may be ineffective in this region. However, Flam and Vestman (2017) focused largely on periods of normal market function. This leaves open the question introduced by Glode (2011): Does the value of high Active Share managers re-emerge specifically during periods of severe market distress? This thesis aims to resolve this conflict by examining whether the insurance value of Active Management materializes in the Nordics when it is needed most.

3.2.4 Dimensions of Active Management

In an earlier chapter, the level of Active Share was discussed in the Nordics. However, the magnitude of Active Management doesn’t itself tell how an active manager takes risks. As Petajisto (2013, p. 5) shows, Active Share might be because of stock picking or factor bets. Therefore, it is critical to analyse Nordic funds through two dimensions: Active Share and Tracking Error.

Even If Active Share is an efficient measure, it does not differentiate between stock picking and systematic risk from taking factor bets. This is highly relevant in the Nordics, where markets are highly concentrated, e.g., Nokia and Novo Nordisk. In such an environment, a high tracking error might occur accidentally simply by excluding a large index constituent, rather than through intentional factor timing. To address this, Petajisto (2013, p.1, 5) divides active managers into categories based on these two dimensions. Diversified stock pickers are funds with high Active Share and low tracking error. Sector weights are close to the index and they are not betting on industries. Consequently, they try to pick undervalued stocks within these industries or sectors. Concentrated stock pickers combine high Active Share and high tracking error (pp. 1, 7). They hold a few stocks and take large positions in individual assets, which leads to higher volatility relative to the benchmark index. Managers who take factor bets focus on factor timing rather than stock selection. They may over- or underweight specific industries or themes. Consequently, they generate large volatility/high tracking error relative to the index, even with small active positions (low Active Share) (pp. 4, 6).

3.2.5 Criticism of Active Share

While Cremers and Petajisto (2009) created Active Share as a measure for predicting fund performance, the metric has faced criticism regarding its robustness and underlying drivers. The most notable critique comes from Frazzini et.al (2016). They claim (p.3) that Active Share highly correlates with small caps, while low Active Share funds correlate with large caps. Furthermore, authors argue that there is no statistical difference between closet indexers and stock pickers in total returns (p. 3). This contradicts evidence presented by Petajisto (2013) that stock pickers have better returns than closet indexers. Furthermore, Frazzini et al. (2016, pp. 7-8) highlight that the outperformance of high Active Share funds is driven by the performance of their benchmark rather than managerial skill. They show that when funds are compared with the same benchmark, higher Active Share does not reliably predict higher returns. Additionally, they conclude that Active Share measures active risk rather than skill and deviation from the benchmark is unlikely to lead to outperformance by itself.

Cremers and Pareek (2016) addressed this criticism by expanding the study to include the turnover rate of funds. Their main finding is that Active Share works, but only under specific conditions. They found that among high Active Share portfolios, only the funds with patient investment strategies, defined as holding durations over two years, outperformed the markets (pp. 288, 304). In contrast, funds that traded frequently underperformed, even if they had high Active Share. This indicates that high turnover destroys value (p. 288). Furthermore, authors note that patience alone is not adequate since low Active Share funds underperformed on average even when using patient strategies (p. 288). These excess returns are explained by the fact that markets have only a limited amount of arbitrage capital devoted to patient and active investment strategies (p. 288). Finally, the authors state that Active Management requires investors to be patient. Such investor patience might be rare, as both fund managers and their investors may need to wait years before getting rewarded for their patience (p. 306).

3.2.6 Active Share in Small Open Economies

Active Share studies are mainly concentrated in U.S. stock markets, where markets are diversified compared to smaller, more concentrated markets such as the Nordics. In such markets, fund managers face a dilemma: holding the largest constituents reduces Active Share while excluding them creates massive tracking error. Secondly, liquidity constraints have an impact on the operations of Nordic mutual funds. Pástor et al. (2015, pp. 23-24) demonstrate that as the total size of the active mutual fund industry expands, a fund's ability to outperform passive benchmarks significantly diminishes**.** Funds face higher transaction costs and greater price impact, which hinders their ability to outperform their benchmarks.

In the context of this study, these structural limitations suggest that Frazzini et al.'s (2016) criticism regarding benchmark bias could be true in the Nordic region. Achieving high Active Share often may require a fund manager to underweight the largest constituents and overweight smaller, less liquid companies. This study controls for this by using capped indices and specific country benchmarks, minimizing the benchmark bias. Furthermore, to ensure that any potential outperformance is driven by managerial skill rather than small-cap tilt, the empirical methodology relies on the Carhart four-factor model. By controlling for the size factor through the SMB factor, the analysis isolates true active performance from structural exposures. During the 2022 crisis, high Active Share might not only reflect managerial skill but also higher exposure to small-cap risk and liquidity risk. This is important, as during crises, portfolio managers may prefer stocks with high liquidity and therefore penalize stocks that high Active Share managers are holding. To isolate managerial skill from the size premium, the empirical models use the size (SMB) factor from the Carhart (1997) four-factor model, ensuring that results are not driven by small-cap bias.

According to Directive 2009/65/EC (UCITS IV), active funds face specific constraints in the EU. The fund may not invest more than 10% of its assets in transferable securities or money market instruments issued by the same body. Due to Nordic markets being highly concentrated, active funds are legally prevented from holding dominant constituents like Novo Nordisk if they exceed 10%. To avoid calculating artificial Active Share driven by regulatory compliance, this study uses capped indices as a benchmark. These indices limit the weight of a single constituent to 10%.

3.3 Active Management and Active Share during Crises

Glode (2011, p. 548) presents an alternative view to the standard view of underperformance. He states that skilled fund managers can act as insurance against "bad states of economy" (p. 547). He argues that underperformance of active funds is a feature that investors are more willing to pay a premium (fees) for this kind of "insurance" (p.548).

Fund managers can request more fees that are higher than expected returns because investors are happy to pay for this kind of insurance (p. 14). The core intuition of his model is that a skilled manager will focus their efforts on generating returns when investors' marginal utility is at its highest, for example, during a crisis or market crash (p. 2). This aligns with prospect theory introduced by Kahneman and Tversky (1979), who argue that losses loom larger than gains (p. 279). Furthermore, they find that investors tend to overweight low probabilities, which explains why insurance is attractive for rare events such as a financial crisis or the 2022 crisis (p.263). Additionally, performance metrics like alpha fail to capture the value of these state-dependent returns. It leads skilled managers to "wrongly appear to underperform" on average. Article suggest that the true test to managers skill is not their average performance but their performance when it matters most, during “bad states of economy” (Glode, 2011, p.547).

The second perspective, which complements the theory of Glode (2011), relates to the efficient market hypothesis during the crisis. While EMH, introduced by Fama (1970), posits that security prices fully reflect all available information, the validity of this assumption can be questioned under conditions of extreme market uncertainty, in this case, the beginning of the COVID-19 pandemic and after the Russian attack on Ukraine in 2022. Geopolitical shocks, such as the Russian invasion of Ukraine, can flood the market with sudden information. Combined with investor panic, this can trigger severe market overreactions and systematic mispricing. In these situations, the efficiency of markets could temporarily weaken and therefore open opportunities for active fund managers who can determine these mispricings from the intrinsic value of the company.

This suggests that temporary market dislocations may create opportunities for skilled managers. Shiller (2003, p. 84) argues that market volatility is driven by things such as “sunspots”, “animal spirits” or mass psychology rather than underlying economic data. He commented on the theory of feedback models that price drops could lead to increasing pessimism and selling leading prices to unsustainable low levels (p.91). In the context of these severe market shocks, this framework suggests that immediate market decline was an overreaction led by uncertainty and fear, creating a window of mispricing for active managers. Shocks such as the COVID-19 shock in 2020 and the geopolitical shock in 2022, therefore offer a natural setting to test whether pricing temporarily from standard EMH assumptions. Furthermore, market inefficiency extends beyond volatility. Modigliani and Cohn (1979, p. 35) noted that markets can be systematically irrational, particularly during periods of high inflation. They concluded that the results are “hard to swallow” yet only hypothesis was supported with empirical data. This framework creates a theoretical framework for Active Management; if the markets make systematic errors during inflation shocks, theoretically skilled active managers should be able to exploit these mispricings. Therefore, these two distinct crises provide an optimal opportunity to test whether active managers can benefit from these behavioral biases and generate considerable risk-adjusted returns when markets are led by fear.

Under Glode's (2011) framework, investors may accept higher fees if active funds perform relatively better during market downturns. Behavioral finance offers a mechanism for how this insurance value is created. According to Shiller (2003) and Modigliani and Cohn (1979), markets often react irrationally to crises, driven by mass psychology or inflation illusions. Consequently, when the market irrationally creates mispricing, a skilled manager can create alpha. Therefore, if the insurance hypothesis holds, high Active Share funds should perform relatively better during times of crisis. Petajisto (2013, p. 27) confirms that active stock selection is indeed most successful at times of high cross-sectional dispersion in stock returns. Since crises are typically characterized by high volatility and dispersion, this suggests that active managers have the genuine opportunity to fulfil the insurance function described by Glode. Kosowski (2011) found that active mutual funds underperform on average. However, this underperformance is due to statistically significant negative risk-adjusted returns during expansion periods. On the contrary, during recession periods, risk-adjusted returns are positive. This performance aligns perfectly with insurance theory presented by Glode (2011), suggesting that the value of Active Management is state-dependent and delivers alpha when investors' marginal utility is at its highest during crises.

However, empirical evidence on insurance value remains debatable in recent crises. Pástor and Vorsatz (2021, p. 24) found that active funds failed to act as a safe haven and generally underperformed passive benchmarks during the COVID-19 crisis in U.S. markets. However, a critical limitation of this finding is that it treats active funds as a homogenous group. As shown by Cremers and Petajisto (2009), a significant portion of active funds are closet indexers who typically underperform net of fees. By including these in the analysis (Pástor and Vorsatz, 2021), results may be biased. Therefore, it is essential to filter out closet indexers to test whether Active Management truly provides insurance value. This study filters out closet indexers by implementing Active Share.

3.4 Hypothesis development

Based on the theoretical framework and empirical findings discussed in earlier sections, this chapter formulates three main hypotheses to examine the behavior and performance of Nordic active funds during two consecutive crises: the COVID-19 crisis and the Russian invasion of Ukraine, followed by an inflationary period.

Previous literature presents conflicting views on the value provided by Active Management. While Fama and French (2010) conclude that Active Management is a zero-sum game where fees destroy any potential alpha, Cremers and Petajisto (2009) argue that this underperformance is driven by closet indexers. They argue that fund managers with high Active Share possess stock-picking skills that remain over time. In concentrated markets such as the Nordics, liquidity constraints and the dominance of a few larger companies, such as Novo Nordisk and Equinor, create a challenging environment for active managers. However, if Active Share can identify manager skills rather than risk-taking, most active funds should be able to justify their fees even in this environment. The first hypothesis tests the general value proposition of Active Management.

H1: ***High Active Share funds generate positive net alpha***

The main tension in literature is between EMH and the behavior of stock markets during the crises. While markets are mostly efficient, Shiller (2003) and Modigliani and Cohn (1979) suggest that crises can cause behavioral biases and mispricing. Later, Glode (2011) provided a theoretical framework for Active Management, suggesting that active managers act as insurance during market downturns and deliver their best relative performance when investors' marginal utility is highest. This study divides the crisis into two phases, the initial shock period and the macroeconomic adjustment period. Based on the hypothesis by Glode (2011), skilled managers should be able to exploit these crises and gain better returns than the benchmark index. The COVID-19 pandemic and the

2022 geopolitical crisis created fundamentally different market conditions. The former was a sudden shock driven by a fear and liquidity constraints while the latter triggered a prolonged inflationary regime shift. Because of these contrasting environments, this study tests the protective value of Active management separately for each crisis with the following hypotheses:

H2A: ***Active Share is positively associated with net alpha during the COVID-19 crash.***
H2B: ***Active Share is positively associated with net alpha during the 2022 geopolitical crisis.***

Lastly, it is important to test how managers react to market stress. Petajisto (2013) suggests that fund managers may reduce their activeness during a crisis to minimize career risk when market uncertainty rises. Testing this behavioral shift presents a methodological limitation: fund holdings and consequently Active Share are reported on semi-annual basis. Because of this reporting lag, immediate intra-month portfolio adjustments during sudden panic (such as March 2020) are not instantly captured in the data. To test this behavioral shift, the last hypothesis is as follows:

H3: ***Average Active Share decreases during crisis periods.***

4 Data and Methodology

The data period (2017–2024) includes the COVID-19 market crash of early 2020 and the 2022 geopolitical crisis. These two crises were fundamentally different. The COVID-19 pandemic represented a sharp liquidity shock, deflationary fears and massive central bank intervention. The 2022 geopolitical crisis, triggered by the Russian invasion of Ukraine, created a completely different market environment characterized by persistent inflation, energy disruptions and a shift toward restrictive monetary policy.

The periods 2017–2019 and 2023–2024 serve as benchmarks of relative market stability in this study. The pre-pandemic era (2017-2019) represents a time of low interest rates and steady economic growth, while the post-2023-2024 period reflects a new normal of higher interest rates. By isolating these two shock periods from the benchmark, this study can more accurately test the insurance hypothesis of Glode (2011). It is expected that active managers can deliver the highest value during the high marginal utility states of 2020 and 2022.

4.1 Crisis description

Crisis periods were selected objectively by using market and macroeconomic data. Two distinct crisis periods occur during the data (2017-2024) period: firstly, the COVID-19 pandemic in 2020 and the geopolitical crises in Ukraine in 2022. These two events represent fundamentally different market environments, providing a robust testing ground to examine the protective nature of Active Management during market downturns.

The first crisis, the COVID-19 pandemic in the spring of 2020, was characterized by a liquidity and fear shock. As illustrated in Figure 1**,** the VIX index shows that the index spiked to over 80 points in March 2020. This large surge indicates a brief but extreme period of market panic, volatility and sell-offs, contrasting largely with the relatively stable market conditions in earlier years. Therefore, the crisis period for this event is short-lasting, from March 2020 to June 2020.

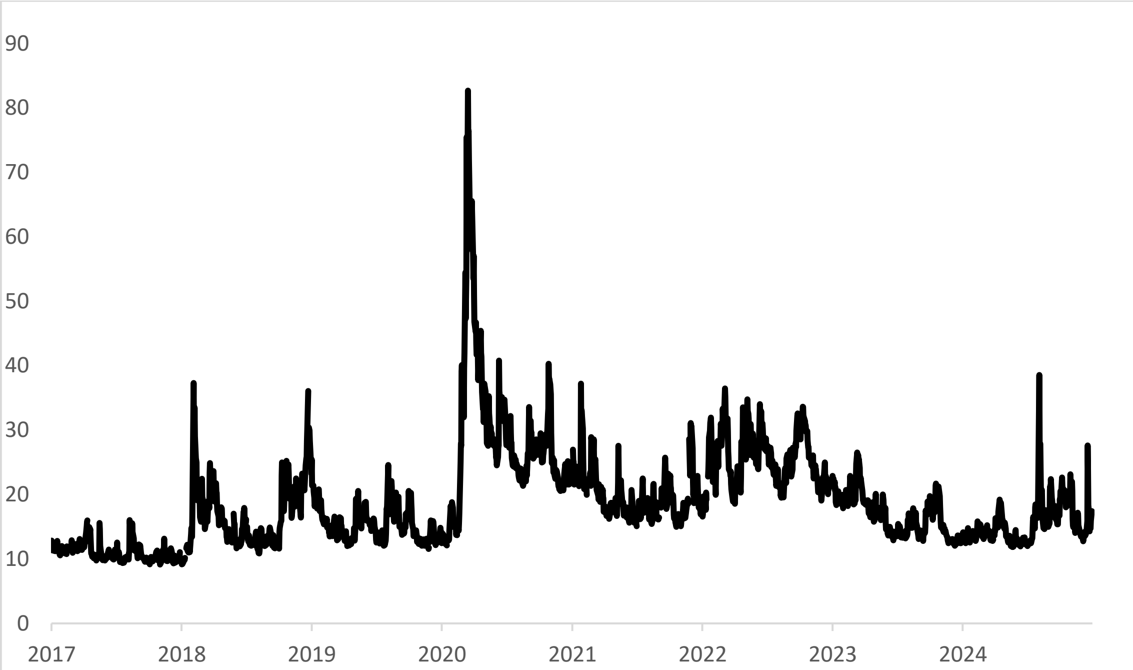

Figure 1 VIXCLS index

In contrast, the second crisis represents a more prolonged macroeconomic regime shift triggered by the Russian invasion of Ukraine in February 2022. The geopolitical conflict caused a severe energy supply shock in Europe. This is visible in Figure 2, which shows the surge in European natural gas prices (Dutch TTF) during the summer and autumn of 2022 as supply chain disruptions hit the market.

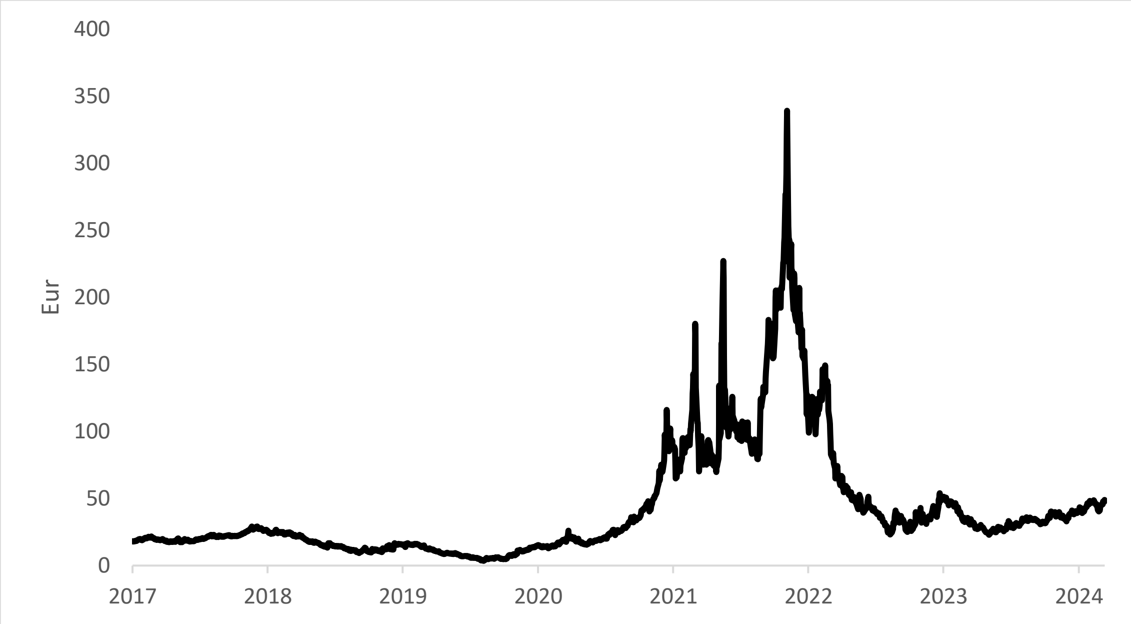

Figure 2 Dutch TTF Natural Gas Future prices

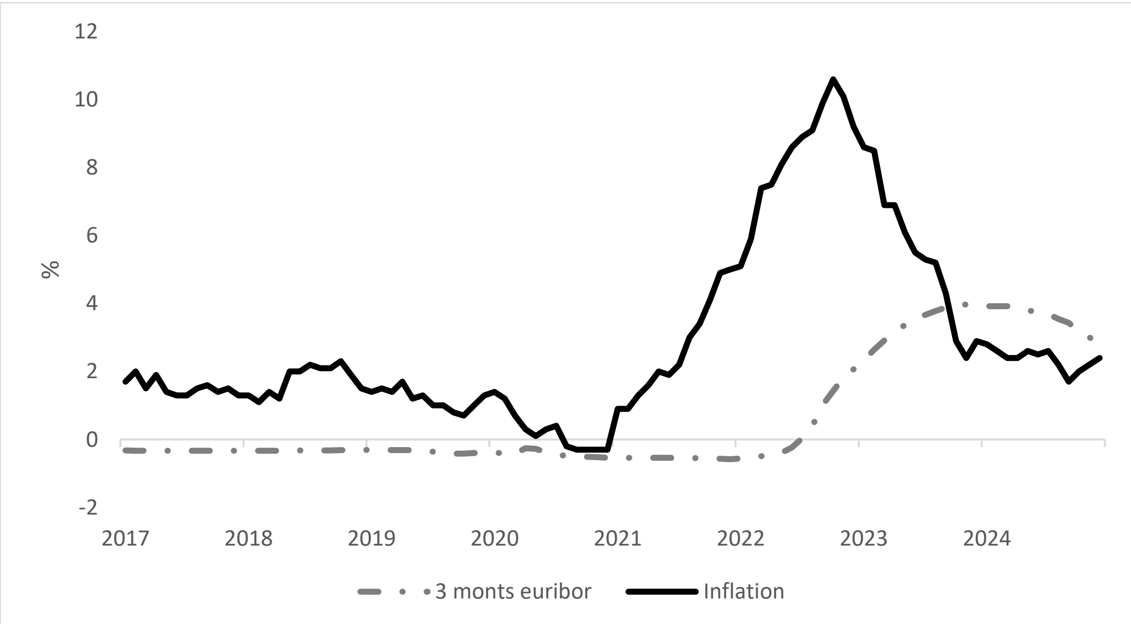

Figure 3 EU inflation measured by overall index and 3-month Euribor

This energy crisis translated into increasing customer prices measured by the overall index in the EU area, as figure 3 shows**.** Inflation accelerated quickly through 2022, forcing central banks to tighten monetary policy. Unlike the short-term panic of 2020, the 2022 crises fundamentally altered the cost of capital and the macroeconomic landscape. The second crisis period covers the whole of 2022 (February to December), as the event was not a short-term panic. Rather, it represented a long-lasting bear market.

4.2 Data

The observation period (2017-2024) is divided into two market shocks. First, the COVID-19 pandemic in early 2020 caused a spike in market volatility. Later, in February 2022, Russia launched an invasion of Ukraine, marking the end of the long bull period and triggering a structural shift in the macroeconomic environment.

Fund net asset values and expense ratios were retrieved from Refinitiv DataStream. Fund return data, founding dates and composition were retrieved from the Bloomberg terminal. Performance of the mutual funds is measured using the net total returns. It considers the reinvestment of dividends. Carhart factors and risk-free rate were retrieved from Kenneth R. French's data library. All data was converted to USD, as Kenneth R. French data uses U.S. dollars. The selection of this risk-free rate is used since all fund and benchmark returns were converted to U.S. dollars and it is necessary to match the Carhart four-factor model data using the USD risk-free rate to ensure consistency. Market premium is constructed manually for the study using returns of theoretical benchmark indices. The one-month risk-free rate, obtained from the French Data Library, is subtracted from this market return.

Due to a lack of composition data for indices, funds are benchmarked against their respective local country investable broad index funds rather than a single common pan-Nordic benchmark, such as the VINX All-Share. Finnish funds are compared to the Nordea Suomi Indeksi, Swedish funds to the Länsförsäkringar Sverige Indexnära, Norwegian fund KLP AksjeNorge Indeks and Danish fund Bank Invest Danske Aktier Indeks. Using actual index funds as benchmarks is methodologically justified from an investor's perspective. This shows the true cost to investors after fees, including transaction costs, tracking error and management fees. This methodological choice is critical for the validity of the Active Share measure. Comparing a single-country fund to the Nordic index can inflate Active Share due to country allocation. For example, a Finnish fund may hold no Swedish stocks. By using country-specific benchmarks, the calculated Active Share isolates the manager's stock selection skill rather than geographical differences. This is consistent with the studies of Cremers and Petajisto's (2009). Because constituent data for the theoretical benchmarks was inaccessible, index funds were used as proxies for both benchmark returns and portfolio compositions. These funds highly correlate with the underlying benchmarks and it ensures that the calculation of Active Share and tracking error remains robust.

The recent EFAMA (2025) report shows that Nordic countries have the highest adoption rate of sustainable investments in Europe. In Sweden, the market share of the Article 8 funds is almost 90%. Länsförsäkringar Sverige Indexnära uses Article 8 classification for sustainability. It is essential for the Swedish benchmark to be an Article 8 benchmark, as the entire fund market is dominated by these funds.

For Norway, an index using the Article 8 classification is selected as a benchmark. This reflects the strategic policy of the country's biggest institutional investor. KLP has stated its strategy to integrate sustainability metrics broadly across its whole fund offering. Most of its funds are classified in Article 8 or Article 9 categories (KLP, 2024). When Norway's biggest pension fund and index investor makes the Article 8 classification standard for its own basic indices, it defines the true opportunity cost that investors face in the market. EFAMA (2025) reports that the majority of Norwegian funds' market share (69% in Q4 of 2024) exhibits Article 8. This strengthens the rationale behind using the Article 8 classified fund as a benchmark.

The Danish fund market is largely divided. According to EFAMA (2025), Article 8 funds accounted for approximately half of the market share at the end of 2023 and 2024. It is reasonable to assume that sustainable funds did not hold most of the market at the beginning of the data period in 2016. Because of this, selecting an Article 6 benchmark, the Danske Aktier Indeks, is a safe and logical choice. This index does not use extensive sustainability exclusions, making it a realistic baseline for the entire sample period.

Passive funds tracking the broad index of Finnish stock markets are typically classified as Article 6. This is largely explained by the narrow and highly concentrated structure of the local market. Historically and currently, the Helsinki stock exchange is heavily weighted towards specific industries, such as the forestry, energy, and heavy machinery sectors, where the weight of single stocks can be disproportionately large. If Article 8 exclusion criteria were used in such markets, which are concentrated in heavy machinery and high-emission sectors, the remaining index would lose the ability to represent Finnish general stock markets. Article 8 compliance often requires negative screening based on carbon emissions, fossil fuel exposure and other sustainability metrics (Danske Invest, 2025). Applying these rules to the Finnish markets would force the exclusion of major domestic large-cap companies, making the index a nonrepresentative benchmark for passive investors.

The Sustainable Finance Disclosure Regulation was implemented in March 2021 by the European Union to enhance market transparency and direct capital flows into more sustainable investments. According to the European Commission (2025), the regulation imposes comprehensive sustainability disclosure requirements on financial market participants and financial advisers. The current SFDR status is utilized in this study as a proxy for a fund's historical investment strategy. This approach is a methodological necessity; therefore, the study operates on the assumption that a fund currently classified as Article 8 applied similar ESG and exclusion criteria historically.

Utilizing the actual index funds as benchmarks provides a more realistic benchmark for performance evaluation. Unlike theoretical indices, which assume zero transaction costs and no management fees, these proxy funds have minor costs and tracking errors that investors would encounter. Cash is regarded as an active decision and, therefore, included in the data.

The sample consists of the largest actively managed domestic equity funds (based on total net assets at the end of the year 2016) in each country. The sample selection was constrained by the availability of fund composition data. This resulted in a sample size of 63 funds. Selection excludes funds with investments on a pan-Nordic or global scale. To mitigate the bias toward large-cap stocks, the regression model controls for the size factor and fund size. The sample was limited to funds investing in mid- and large-cap firms. As Cremers and Petajistö (2009) argued that Active Share is a holding-based measure, the investing universe was measured by Bloomberg's Mkt Cap Focus (Holdings Based) measure. This eliminates inconsistencies between stated prospectus objectives and actual investments and effectively controls for style drift. A Traditional index-based product was intentionally retained to serve as a methodological baseline.

Data will be retrieved from December 2016 to the end of 2024. The data set includes dead funds and retains them until the period up to their closure. This choice eliminates survivorship bias, which otherwise would inflate the historical performance of active managers by ignoring failed managers. Data sample includes 13 funds from Denmark, 15 from Finland, 18 from Norway and 16 from Sweden.

4.2.1 Data limitations

The primary limitation of this study is the reliance on semi-annual fund composition data. This approach does not capture every trade during the period from 2017 to 2024, but the timeframe is enough to reveal structural shifts in management styles during both the COVID-19 and the 2022 geopolitical crises. Turnover ratio was not included as data was not available.

Because raw constituent data for the theoretical benchmarks was inaccessible, index funds were used as proxies for both benchmark returns and portfolio compositions. These funds highly correlate with the underlying benchmarks and it ensures that the calculation of Active Share and tracking error remains robust

4.3 Methodology

The data used in this study are panel datasets, as they consist of observations for multiple funds across time periods. A fixed effects model was used over a random effects model after conducting Hausman tests. The models are estimated using panel least squares with a fixed effects model to control for time-invariant unobserved fund characteristics, such as manager skill or brand quality. To address potential heteroskedastic and cross-sectional correlation, all regressions are estimated using White cross-sectional standard errors.

To ensure the robustness of the performance evaluation, the Carhart (1997) four-factor model (market premium, size, value and momentum) is utilized to control for systematic market risks. This ensures that results reflect stock selection skills rather than factor bets. To empirically test the hypotheses, the panel regression analysis is divided into four distinct models. In the first three performance models, the dependent variable is the fund's monthly excess return over the risk-free rate

Model 1: Baseline performance

The baseline relationship between Active Share and fund performance is estimated using the following model:

(1) $R_{i,t} - R_{f_t} = \alpha_i + \beta_1 AS_{i,t-1} + \beta_{2,i} MktRF_t + \beta_{3,i} SMB_t + \beta_{4,i} HML_t + \beta_{5,i} MOM_T + \varepsilon_i, t$

Where $AS_{i,t-1}$is the fund's Active Share at the beginning of the period. The$MktRF_t$ market risk premium SMB is the size factor and HML is the value factor. α_i captures the fund-specific fixed effects to control for time-invariant unobserved heterogeneity across funds. Model 1 tests hypothesis 1 over the full sample period (2017-2024) to determine the baseline relationship between Active Share and fund performance.

Model 2: Fund-Specific Controls

To control and ensure that results are not driven by fund traits, Model 2 uses fund-specific control variables:

(2) $R_{i,t} - R_{f_t} = \alpha_i + \beta_1 AS_{i,t-1} + \beta_{2,i} MktRF_t + \beta_{3,i} SMB_t + \beta_{4,i} HML_t + \beta_{5,i} MOM_T + \beta_{6,i} Size_{i,t-1} + \beta_{7,i} age_{t-1} + \beta_{8,i} Exratio_{i,t-1} + \beta_{9,i} TE_{i,t-1} + \varepsilon_{i,t}$

The second model builds upon the first model by adding fund-specific lagged control variables: natural logarithm of fund size ($Size_{i,t-1}$), natural logarithm of fund age (age_{t-1}), expense ratio ($Exratio_{i,t-1}$) and tracking error ($TE_{i,t-1}$). Including these variables ensures that the relationship between Active Share and performance is not driven by other fund characteristics.

Model 3: The State-Dependent Insurance Value

To test the state-dependent nature of Active Management, Model 3 incorporates crisis dummy variables and their interaction terms:

(3) $R_{i,t} - R_{f_t} = \alpha_i + \beta_1 AS_{t-1} + \beta_2 \left(AS_{i,t-1} * D_{Covid,t}\right) + \beta_3 \left(AS_{i,t-1} * D_{Ukraine,t}\right) + \Theta_1 D_{Covid,t} + \Theta_2 D_{Ukraine,t} + \sum_{k=1}^{4} \gamma \kappa F_{k,t} + \sum_{J=1}^{K} \delta_{\mathrm{j}} X_{j,i,t-1} + \varepsilon_{i,t}$

This model tests the state-dependent nature of Active Management (Glode, 2011) by evaluating both the volatility shock (Hypothesis 2a) and the prolonged 2022 geopolitical and inflationary crisis (Hypothesis 2b) using a single framework. Two dummy variables ($D_{Covid,t}$ and $D_{Ukraine,t}$) and their interaction terms$\left(AS_{i,t-1} * D_{Covid,t}\right)$ and $\left(AS_{i,t-1} * D_{Ukraine,t}\right)$ with Active Share are added to the equation.

Model 4: Behavioral Shifts During Crises

Fourth regression tests Hypothesis 3, which assumes that fund managers reduced active risk during market crises, a panel regression was conducted with Active Share as the dependent variable:

(4) $Active\ share = \alpha_i + \beta_1 D_{Covid,t} + \beta_2 D_{Ukraine,t} + \varepsilon_i$

where μ_1 represents fund-specific fixed effects and ($\beta_1 D_{Covid,t}$ and $\beta_2 D_{Ukraine,t}$) represents the crisis dummy variables.

Active Share was calculated semi-annually. It involved a multi-step manual process. For each of the 63 funds in the sample across countries, raw holding data was extracted and manually matched with holdings of the proxy index. This required decomposing both the active funds and the benchmark indices into individual security weights to calculate the absolute deviation for each stock. Tracking error was calculated differently. While Active Share is a holdings-based snapshot, portfolio tracking error is a return-based metric that measures active risk taken by the fund manager. In this study, tracking error is calculated as the standard deviation of the monthly excess returns of the funds relative to their stated benchmark. A 36-month rolling window of historical returns is used. The resulting monthly standard deviation is then annualized by multiplying it by the square root of 12. Pre-sample data was collected to calculate tracking error. Mismatch of reporting frequencies remained a challenge. While fund returns are reported monthly, portfolio holdings required to calculate Active Share are only available semi-annually. The semi-annual Active Share observations were carried forward for the subsequent six months. For instance, the Active Share calculated at the end of December applied to funds' monthly observations from January to June. This approach assumes that fund managers' active bets remain relatively constant between reporting dates.

To ensure the robustness of the empirical results and to mitigate the impact of potential outliers, excess return, tracking error and expense ratio were winsorized at the 1st and 99th percentiles. By capping the extreme values, the influence of outliers is limited while preserving the total number of observations in the panel. To test multicollinearity between independent variables does not bias the regression results, a Principal Component analysis was conducted. The analysis provided a condition number of approximately 6.93. It confirms there is no significant multicollinearity between Active Share, Tracking Error and factor loadings.

4.4 Variable selection

As Cremers and Petajisto (2009) and Petajisto (2013) show, Active Share and Tracking error are necessary to distinguish truly active stock pickers from closet indexers. Active Share is the key independent variable.

Evans (2010, p. 1584) has shown that new funds return exhibits incubation bias. To control for this bias, fund age is included as a control variable, which imitates Pástor et al.'s (2015) methodology. Fund size is measured as the natural logarithm of total net assets, following Pástor et al. (2015, p.42). This transformation assumes that performance is driven by proportional change rather than absolute changes in fund size. The expense ratio is included as a control variable, as management fees and administrative expenses directly reduce the net returns delivered to investors. Controlling for the expense ratio is essential to ensure that the analysis inspects the manager's actual skill rather than the negative impact of fund costs.

The Carhart (1997) four-factor model (market, size, value and momentum) is used to control for general market risks. This ensures that any observed outperformance comes from true stock picking skill rather than exposure to these factors. Following the critique by Frazzini et al. (2016), it is important to control for exposure to small-cap stocks.

To investigate the performance of Active Management during the crises, the crisis dummy variables (COVID-19 and the 2022 geopolitical crisis) and their interaction terms with Active Share are included in the models. This allows for testing the Glode (2011) insurance theorem. The dependent variable in the panel regressions is the fund's monthly excess return, calculated as the fund's net return minus the risk-free rate. By regressing excess returns on the risk factors simultaneously with fund controls, the model directly estimates the conditional outperformance generated by the manager's skill, while controlling for the returns driven by market, size, value and momentum exposures.

5 Empirical findings

This chapter presents details of the panel data regression results.

5.1 Descriptive statistics of the sample

Table 2 presents descriptive statistics for the full sample of 4405 observations.

Table 2 Descriptive statistics Winsorized data

Variable	Mean	Median	Min	Max	Std. Dev.	N
Excess Return (%)	0.48	0.66	-17.42	14.54	5.88	4405
Active Share (%)	44.25	43.43	3.2	95.13	16.16	4405
Tracking Error (%)	4.44	4.2	0.96	9.69	1.69	4405
Fund Size (MUSD)	556.16	176.75	27.52	6032.08	914.26	4405
Expense Ratio (%)	1.28	1.32	0.21	2	0.45	4405
Fund Age (Months)	270.84	269.57	37.83	531.57	102.02	4405
Market Premium (%)	0.49	0.66	-23.86	24.02	6.03	4405
SMB (%)	-0.11	-0.38	-4.22	5.03	1.7	4405
HML (%)	0.03	-0.2	-11.3	12.09	3.07	4405
MOM (%)	0.59	0.7	-18.39	8.5	3.2	4405

The average Active Share across the data period is 44%, with a standard deviation of 16%. It indicates significant variation in management styles within the Nordic market. The average annual expense ratio is 1.28%, which is significantly larger than passive alternatives. The sample has substantial dispersion in fund sizes. The mean fund size is 556 million USD, while the median is 176.83 million USD. This indicates that the distribution is strongly skewed to the right, where the market is dominated by a few large funds. The sample has a large degree of variation in Active Management levels, with a standard deviation of 16.16% for Active Share. This variation suggests that the dataset is not dominated by a single management style, providing a robust basis for examining the performance differences between low and high-Active Share funds.

Table 3 presents the correlation matrix for the variables used in the empirical analysis.

Table 3 Correlation matrix Winsorized data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) EXCESS_RETURN	1.000									
(2) TRACKING ERROR	0.005	1.000								
(3) SIZE	-0.039	-0.123	1.000							
(4) ACTIVE SHARE	0.008	0.552	0.183	1.000						
(5) AGE	-0.013	-0.068	0.308	-0.059	1.000					
(6) EXPENSE RATIO	-0.009	-0.138	-0.234	-0.258	-0.097	1.000				
(7) MARKET PREMIUM	0.950	0.004	-0.034	0.003	-0.014	-0.009	1.000			
(8) HML	0.033	0.078	0.049	0.003	0.041	0.001	0.056	1.000		
(9) MOM	-0.347	-0.028	-0.011	-0.006	-0.003	0.001	-0.376	-0.481	1.000	
(10) SMB	0.411	-0.044	-0.026	-0.016	-0.017	-0.006	0.394	-0.137	0.020	1.000

The matrix shows that the independent variables are not too correlated. For instance, tracking error and Active Share exhibit a positive but moderate correlation (0.55), which is expected as Active Management typically leads to higher deviations from the benchmark. Fund size and age show a positive correlation, which suggests that Nordic markets have established funds that tend to manage larger amounts of capital. The variables are not overly correlated, suggesting that multicollinearity might not be a major concern.

Figure 4 represents a large picture of the average Active Share of Nordic mutual funds from 2016 to 2024, including two crises (COVID-19 and Ukraine geopolitical crisis).

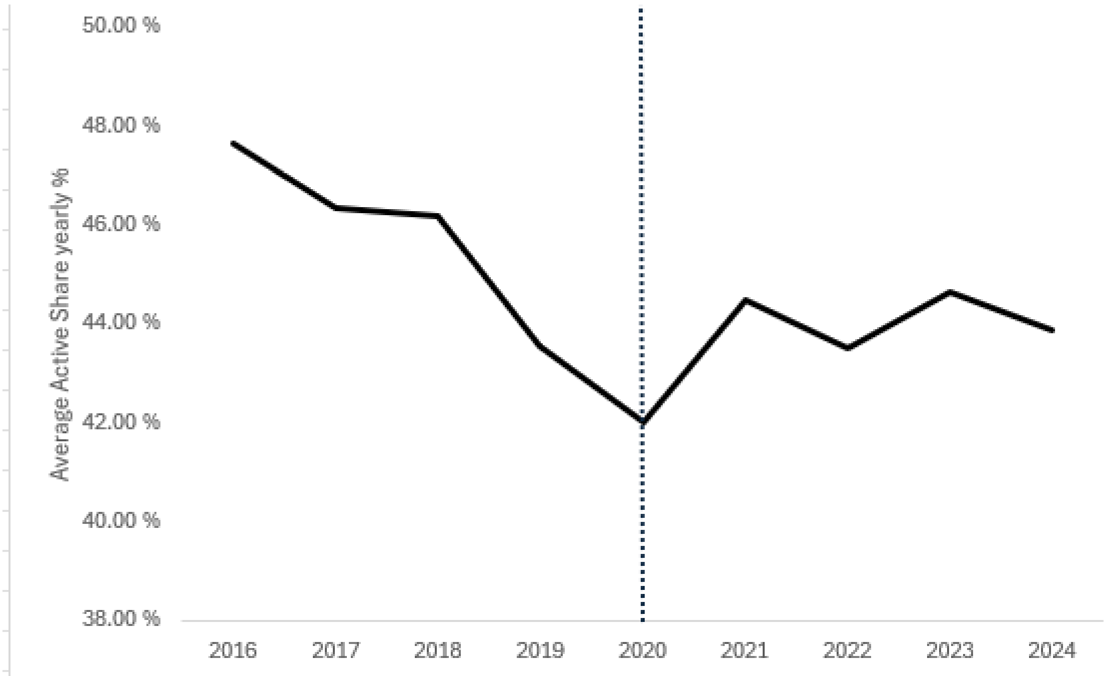

Figure 4 Average Active Share of Nordic Mutual Funds (2016–2024). Data points represent annual averages. The dashed line indicates the year 2020 and the COVID-19 pandemic.

The time-series development of the Active Share Figure 4 reveals a downward trend from 2016 to 2020, where the average dipped to its lowest point of approximately 38% during the COVID-19 pandemic. However, the defensive shift was temporary. Following the market stabilization, the average Active Share began to recover to approximately 45% the following year.

To further examine the impact of the COVID-19 drop, Figure 5 provides a monthly view of the average Active Share from August 2019 to December 2020.

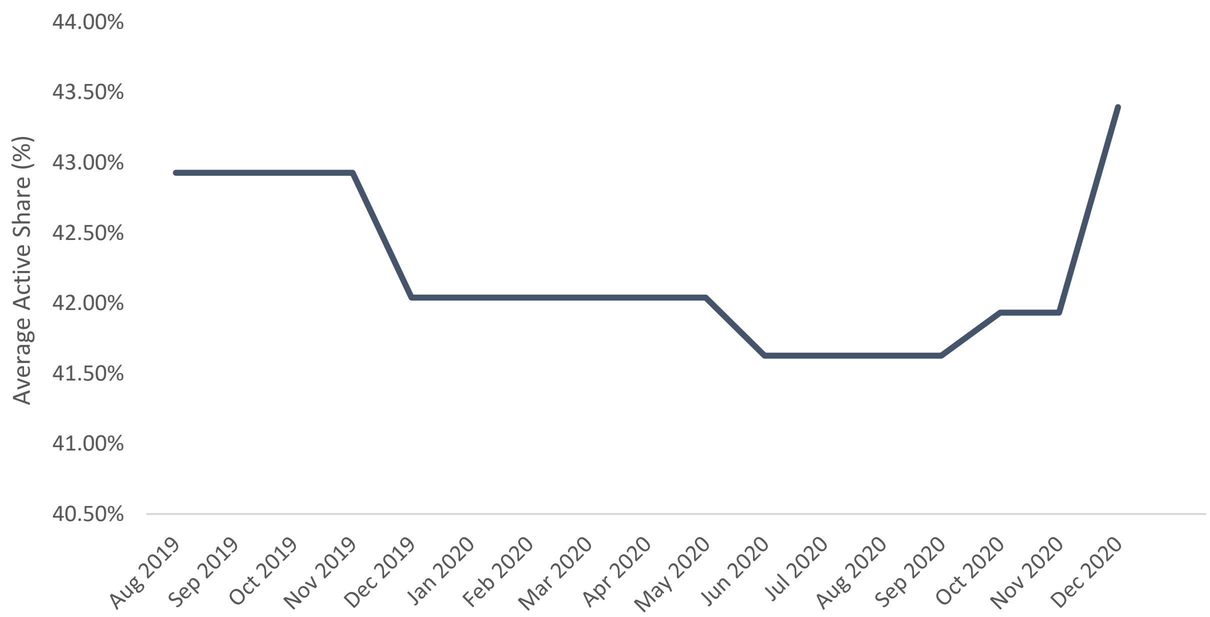

Figure 5 Average Active Share August 2019 to December 2020

The step-like appearance of the graph in Figure 5 is a direct result of the data structure. Because most of the funds report their holdings semi-annually, the Active Share value largely remains constant between the main reporting months (December-June), causing the average to form visible flat periods. However, the minor fluctuations observed between the major reporting dates occur because slight shifts in the monthly average can be attributed to survivorship and sample composition changes, for instance, individual funds exiting the dataset.

Figure 6 illustrates the distribution of the sample funds into different categories based on their average Active Share levels. This distribution provides an overview of the prevalence of different investment styles

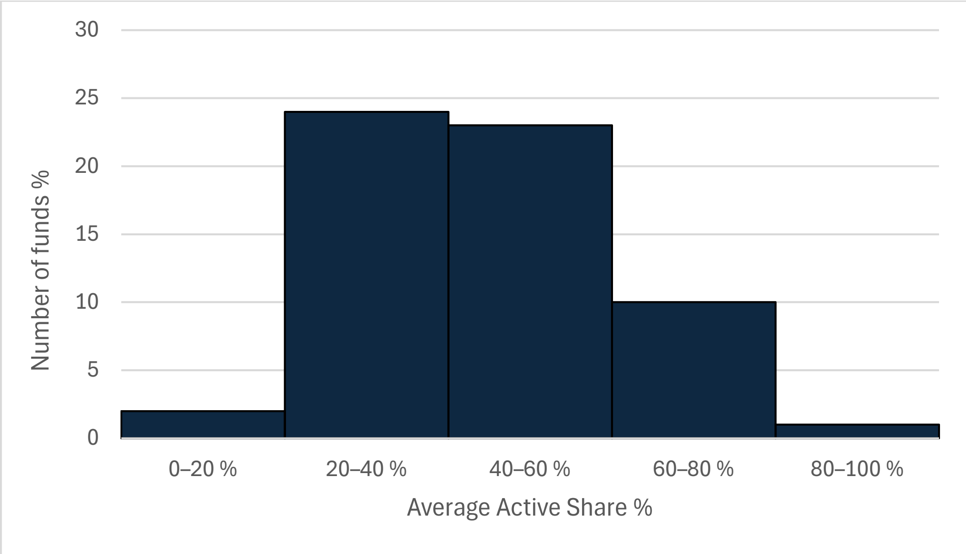

Figure 6 Distribution of funds by average Active Share percentage in the Nordic mutual fund sample. The bars represent the percentage of funds falling into each 20% activity bracket.

The histogram is highly skewed to the left. Most of the funds are concentrated within the 20-40% and 40-60% categories**.** Cremers and Petajisto (2009) classified funds within this range as closet indexers. Truly active funds with an Active Share exceeding 80% represent only a few percentages of the sample, highlighting a tendency toward closet indexing in the Nordic markets.

Active Share does not reveal all dimensions of Active Management. Figure 7 combines Tracking Error with Active Share to get a thorough analysis of the Nordic Active Management space.

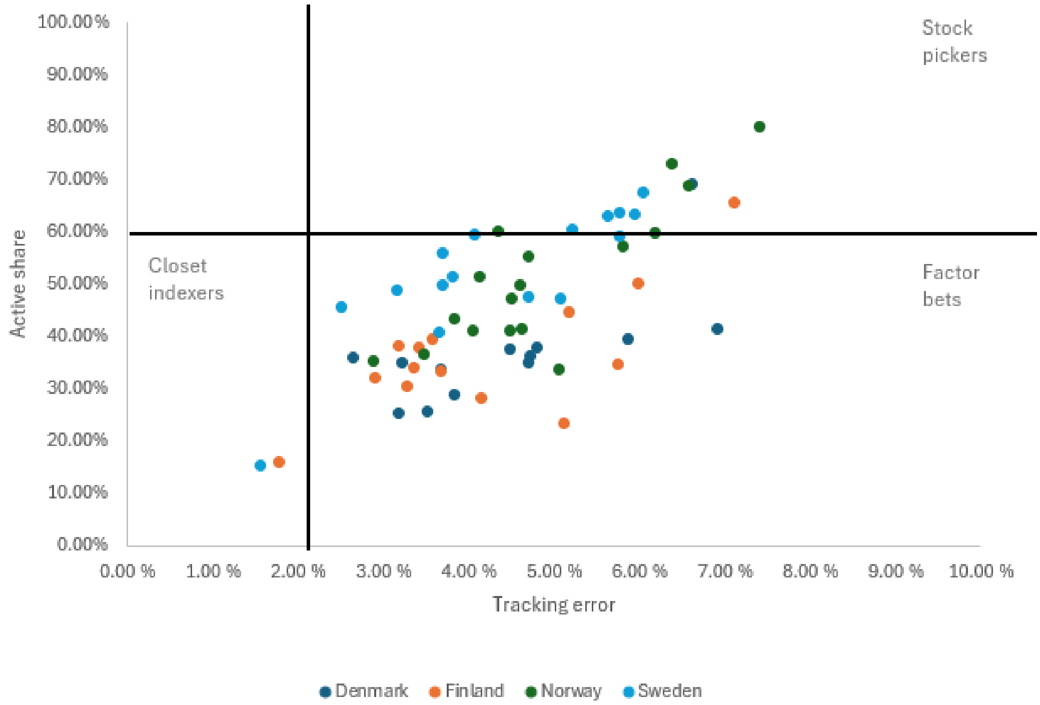

Figure 7 Dimensions of Active Management in the Nordic Mutual Fund Sample. The plot categorizes funds into four quadrants based on Petajisto's (2013) methodology, separated by 60% Active Share and 2% Tracking Error thresholds.

Figure 7 shows that most of the active Nordic equity funds are in the right corner, which is equivalent to the factor bets category (low Active Share, high Tracking Error). This suggests that Nordic fund managers tend to avoid significant deviations from individual security weightings. Instead, they appear to take active positions based on broader market characteristics, such as sector allocations or style factors (e.g., value, size, or momentum). While funds are closer to benchmarks in terms of holdings, their factor tilts or sector allocations lead to higher tracking error and increased volatility compared to their benchmark indices.

Figure 8 presents the development of Active Share in Nordic markets between 2017 and 2024.

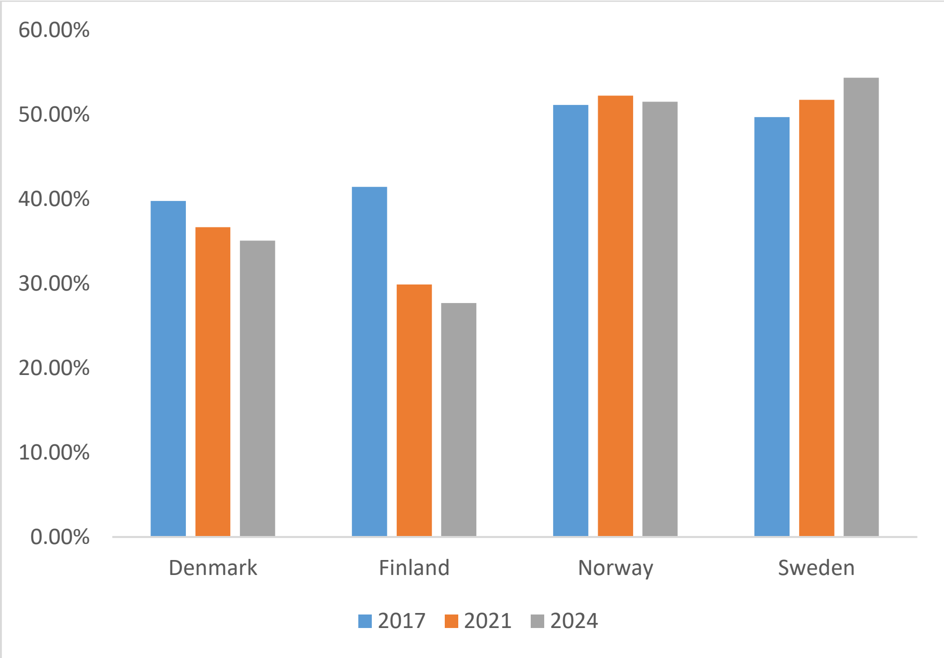

Figure 8 Development of average Active Share in Nordics

The degree of Active Management has risen in Sweden from 2017 to 2024. In Norway, funds have retained their level of activeness. Consequently, the level of activeness has fallen in Denmark and Finland. Level of activeness in Finland may reflect decrease in samples over the years. While in 2017 there were 15 Finnish funds in the sample in 2017 there were 9 left December 2024.

5.2 Baseline results: Active Share and Fund Performance

The reliability of the regression model was tested by the Durbin-Watson test. All three test numbers were close to 2 (2.117, 2.152 and 2.16), suggesting no substantial first-order autocorrelation in the residuals

Table 4 presents the results of panel regressions using the Carhart four-factor model with fixed effects. Model 1 serves as the foundational baseline, estimating the standard Carhart four-factor model without any fund-specific control variables or Active Share, while Model 2 introduces fund-specific control variables (Log Size, Expense Ratio and Age). Model 3 includes crisis dummies and interaction terms to test Glode's (2011) insurance hypothesis. Explanatory power of the models is robust, with adjusted R-squared values around 90% in all models.

Table 4 Regression results the dependent variable is the fund's monthly excess return. The models are estimated using panel data with fixed effects. White cross-section robust standard errors are reported in parentheses. Statistical significance levels are as follows: * p < 0.10, ** p < 0.05, *** p < 0.01

Variable	Model 1 (Baseline)	Model 2 (Controls)	Model 3 (Crises)
Intercept	0.0000	-0.0360	-0.0380
	(0.002)	(0.027)	(0.027)
Active Share lagged	0.0000	0.0020	0.0020
	(0.004)	(0.004)	(0.004)
Market Premium	0.906 ***	0.909 ***	0.907 ***
	(0.019)	(0.019)	(0.018)
SMB (Size factor)	0.150 ***	0.150 ***	0.151 ***
	(0.042)	(0.043)	(0.045)
HML (Value factor)	-0.0260	-0.0340	-0.0200
	(0.025)	(0.027)	(0.027)
MOM (Momentum)	-0.0050	-0.0110	-0.0120
	(0.036)	(0.036)	(0.039)
Tracking Error lagged		-0.0310	-0.0160
		(0.054)	(0.053)
Log Size lagged		-0.0030	-0.0020
		(0.002)	(0.002)
Expense Ratio lagged		-0.0030	-0.0030
		(0.002)	(0.002)
Age lagged		0.010 *	0.010 *
		(0.006)	(0.006)
COVID-19			-0.0020
			(0.003)
Active Share*COVID-19			0.023 ***
			(0.006)
War			0.0010
			(0.004)
Active Share*War			-0.0030
			(0.008)
Observations (N)	4754	4405	4405
Adjusted R-squared	0.899	0.903	0.904
Durbin-Watson stat	2.117	2.152	2.160
Fund specific effects (FE)	Yes	Yes	Yes

Model 1 shows that Nordic stock markets are largely driven by standard market factors, as the adjusted R-squared is 89.9%. In the model, the intercept (alpha) is zero and statistically insignificant, suggesting that on a risk-adjusted basis, the funds perform in line with their benchmarks before accounting for fund-specific characteristics. The loadings in the models reveal the structural risk profile of sampled funds. The market premium strongly drives the returns with a highly significant coefficient of approximately 0.91 in all models, showing that the average market beta of the Nordic mutual funds sample is slightly below 1. A beta of 0.91 demonstrates that these funds are exposed to general market movements but are slightly defensive compared to the broader market. The positive and highly significant SMB coefficient (0.15) confirms that Nordic funds lean towards small-cap stocks. Momentum coefficient (-0.005) suggests that momentum strategies do not contribute to returns in this sample.

Model 2 introduces fund-specific control variables to further examine performance. The most notable observation from the baseline models is the coefficient for lagged Active Share. In all three models, the coefficient for Active Share remains statistically insignificant. Because the coefficient is almost zero, increasing Active Share has no meaningful economic impact on the net returns. For example, a 10% increase in Active Share would boost monthly returns by 0.02 percentage points, confirming that the effect is insignificant. Combined with the insignificant coefficient for Active Share, the empirical evidence does not support Hypothesis 1**.** Under normal market conditions, greater market activity does not mean positive net alpha for Nordic investors. The intercept (alpha) in Model 2 is negative (-0.036) but statistically insignificant. This aligns with Berk and Green (2004 pp. 3-4, 14), where competition drives net alpha toward zero as skilled managers extract the full value of their skill in the form of fees. The insignificant coefficient for the expense ratio (-0.003) suggests that higher fees are not associated with lower net returns. This suggests that fee differences are not systematically associated with net excess returns within this sample.

Consistent with recent findings by Laaksonen (2023) in the Finnish market, it is found that fund size (-0.003) did not have a statistically significant impact on net returns. This contrasts with the theoretical framework of liquidity constraints discussed by Pástor et al. (2015). The explanation for this is that Nordic mutual funds are relatively small globally, meaning they do not face the costs and inefficiencies associated with massive scale

The fund age variable is positive and significant at the 10% level in Model 2 (0.010). This positive coefficient may reflect the survivorship bias, as poorly performing funds are more likely to be liquidated and exit the sample, leaving only the successful funds with proven long-term strategies.

5.3 The value of Active Management during crises (Model 3)

Model 3 (Table 4) controls for COVID-19 and the geopolitical crisis in 2022. In this chapter, these crises and hypotheses 2A and 2B are discussed to see if Active Share provided protection during the time of crises.

5.3.1 COVID-19 Pandemic

The COVID-19 pandemic in the spring represented short-term liquidity and fear shock. According to Glode's (2011) insurance hypothesis, skilled managers should have delivered alpha during this crisis period, as investors' marginal utility for avoiding losses was exceptionally high. Model 3 in Table 4 shows regression results for Active Share during the COVID-19 shock from March 2020 to June 2020. The COVID dummy variable is statistically insignificant, and the coefficient (-0.002) is economically negligible. Therefore, average funds, particularly those with low Active Share in the sample, did not make significant over- or underperformance during the COVID-19 shock. However, the highly significant positive interaction term (Active Share* COVID-19 = 0.023) at the 1% level shows that Active Management, measured by Active Share, did provide downside protection on a risk-adjusted basis. For every 10% increase in Active Share, a fund's risk-adjusted monthly excess return increased by approximately 0.23 percentage points during the COVID-19 crash. This provides empirical support for Glode's (2011) insurance hypothesis, suggesting that funds with higher Active Share delivered stronger relative performance during the crisis. Also, these results provide contrasting evidence for Pástor and Vorsatz's

(2021) study, which found that active funds underperformed during the COVID-19 crisis. They treated active funds as a homogeneous group without measuring specific activity levels. This study isolates the impact of stock-picking intensity. The results suggest that underperformance often associated with Active Management during crises may be partially driven by funds with low Active Share, whereas truly active Nordic managers were able to generate risk-adjusted value.

To visualize performance differences, funds are divided into two categories based on their level of activeness: truly active funds with Active Share over 60% and closet indexers with Active Share under 60%. The following graphs (Figures 9 and 10) will provide a visual comparison of how these two groups performed in different months of spring 2020.

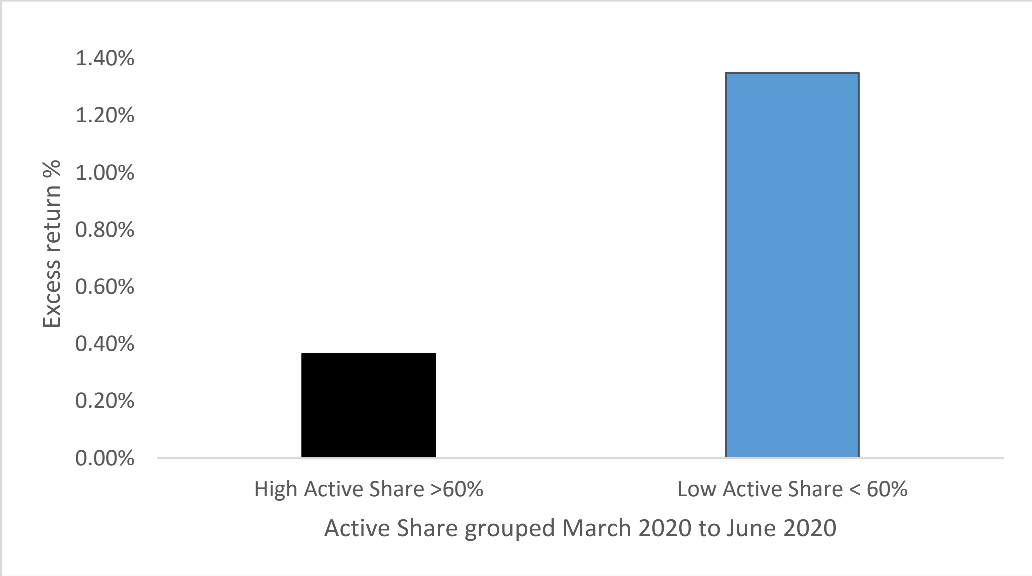

Figure 9 Funds grouped into two categories and their respective returns in % from March 2020 to June 2020 during the COVID-19 pandemic

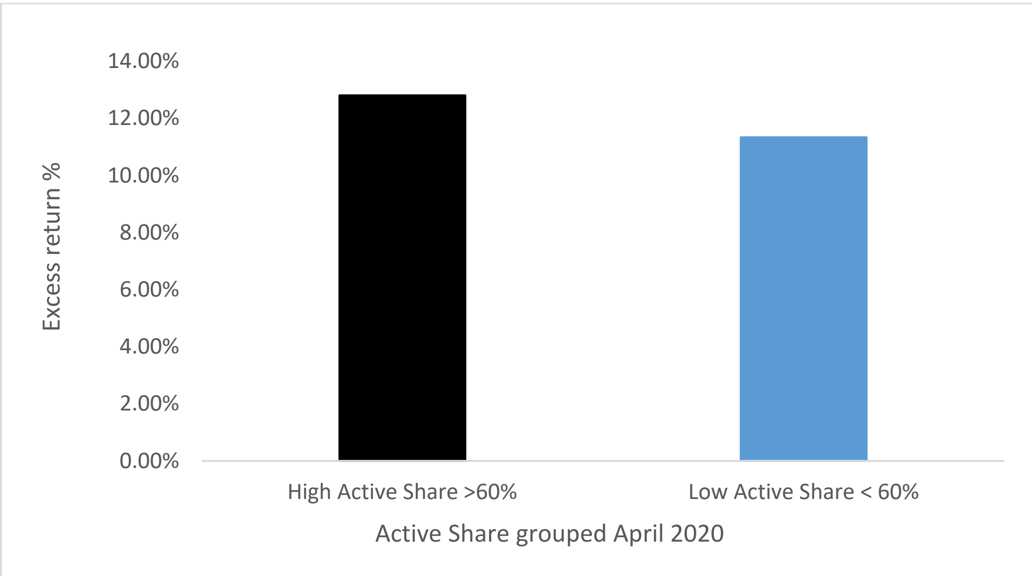

Figure 10 Funds grouped into two categories and their respective returns in % in April 2020 during the COVID-19 pandemic

Graphs show a large contrast: closet indexers significantly outperformed truly active funds **i**n terms of raw excess returns. While high Active Share funds experienced a slightly stronger rebound during the single month of April 2020 (Figure 10, left graph), this short-term bounce was not enough to compensate for their underperformance during the market turmoil. The underperformance of high Active Share funds may be attributed to their structural exposure to small-cap stocks, which suffered during the liquidity shock.

In summary, the results for the COVID-19 period highlight the distinction between absolute returns and risk-adjusted returns. Underperformance in raw returns is due to exposure to structural factors such as exposure to small-cap risk. They delivered statistically significant positive alpha when systematic risk factors were accounted for. Therefore, the insurance value of high Active Share during the COVID-19 crash must be understood in a risk-adjusted context. The active stock-picking successfully mitigated the structural factor losses; without this positive contribution, the raw performance of these funds would have been worse. Active Management acted as a shock absorber. As the interaction term for Active Share and the COVID-19 shock is positive and significant, Hypothesis 2A is supported.

It is important to note that due to the semi-annual reporting of the holdings, the observed insurance value is likely to stem from the quality of pre-existing stock selection rather than intra-month during the shock. As seen in Figure 7**,** Nordic mutual funds are located in the right corner and are characterized as Factor bets. If high Active Share funds were overweight in sectors that proved resilient and were "winners" of the pandemic, such as technology and healthcare, the model might interpret this sectoral success as individual stock-picking skill.

Furthermore, the analysis could have incorporated Tracking Error as a secondary dimension of activity. Because sector bets typically result in higher Tracking Error, including TE-based interaction terms would have allowed for a clearer distinction between pure stock-pickers and factor-based bettors. Additionally, Gonzalez Ehnes et al. (2024, p. 7) found that tracking error approximately doubled for some vehicles, such as the Norwegian country ETF, during the pandemic due to liquidity risks and exchange rate volatility (p. 2). This suggests that the benchmark proxies themselves may have suffered from tracking inefficiencies, potentially inflating the observed relative performance of active managers during the crisis.

5.3.2 The 2022 geopolitical and macroeconomic crisis

The geopolitical and macroeconomic environment of 2022 presented fundamentally different types of challenges for Nordic active managers. The year of the Russian invasion of Ukraine was characterized by rising inflation, the European energy crisis and a shift in central bank monetary policies. Rather than a sudden, systematic shock, 2022 unfolded as a prolonged macroeconomic shock.

Model 3 in Table 4 captures performance during this period. The dummy variable for the 2022 crisis (War) is statistically insignificant with a coefficient of 0.0010. It shows that, on average, the performance of mutual funds did not deviate significantly from the benchmark on a risk-adjusted basis during the year. The interaction term between Active Share and the 2022 crisis is negative (-0.0030) and statistically indistinguishable from zero. This reveals that a higher degree of Active Management did not translate into risk-adjusted outperformance or downside protection during this specific market environment. The empirical results do not provide empirical support for hypothesis 2B.

The results of this study reveal a divergence between the success of active managers during the COVID-19 crash and their failure to provide insurance value during the 2022 crisis. This divergence can be interpreted using Andrew Lo's (2004) Adaptive Market Hypothesis (AMH). According to the AMH, the degree of market efficiency is dynamic and fluctuates based on environmental conditions and the behavior of market participants.

The COVID-19 crash was a sudden liquidity and fear shock, which is clearly visible as an extreme spike in the volatility index (See Figure, 1). It triggered panic, which led to indiscriminate selling and temporarily sidelined arbitrage capital. In the framework of the AMH, this sudden drop in competition is consistent with a temporary decline in market efficiency, which may explain the observed alpha. Because Active Share is measured semi-annually in this study, the positive interaction term during the COVID-19 crash does not necessarily imply that managers engaged in rapid, short- term trading to exploit these mispricings at the market bottom. Rather, it implies that managers who employed a highly active, high-conviction strategy entering the crisis were better equipped to navigate the market turmoil and generate unsystematic alpha. Their pre-existing stock selections and ability to hold undervalued assets through the panic provided downside protection

In contrast, while the 2022 crisis was also triggered by a sudden geopolitical shock, it immediately evolved into a structural macroeconomic regime shift and energy crisis (Figure 2 and 3). According to the AMH framework, market participants rapidly adapted to this new macroeconomic reality. This may suggest that systematic and macroeconomic factors may have dominated stock-specific returns during this period. In such macro environment insurance value of active-stock picking fails to materialize. In the Nordic markets, highly Active Share funds tilt towards small-cap and growth equities. As shown in the results (Table 4), the mutual funds in the Nordic exhibit structural tilt towards small-cap equities. In highly concentrated markets achieving a High Active Share requires managers to underweight mega-cap constituents and tilt their portfolio towards these smaller, longer-duration equities. These long-duration equities are more vulnerable to rising inflation and interest rates as their cash-flows are usually longer in the future. While it might be expected that these funds to underperform during 2022, Model 3 shows their risk-adjusted performance was statistically zero. This occurs because the Carhart four-factor model absorbs the systematic market hit through its size (SMB) and value (HML) factors. While the absolute returns of these funds suffered from rising rates, the managers' stock-picking neither worsened nor mitigated the macroeconomic shock.

Petajisto (2013, p.74) found that the financial crisis hit active funds severely in 2008, leading to broad underperformance in 2008. It was followed by a strong recovery in 2009, and active stock pickers beat their indices in the whole period (2008 to 2009) by 1% and closet indexers continued to underperform. In December 2008, the Federal Reserve initiated massive monetary easing as the target federal funds rate reached its lower bound of zero (Gagnon et al., 2011, p.3).

Both the 2008 financial crisis and the 2022 geopolitical crisis can be described as prolonged macroeconomic shifts. Fundamentally, they were different. While the financial crisis was characterized by massive monetary easing, the 2022 crisis was driven by an energy shock and rapid monetary tightening in an inflationary environment. Rising interest rates penalize long-duration companies, whereas low interest rates support them. The outperformance of high Active Share funds in 2008 might have been partially driven by this favourable duration exposure rather than pure stock-picking skill, just as their failure to provide insurance value in 2022 reflects the severe duration penalty caused by rising rates. Because the Carhart four-factor model may not fully capture the penalty placed on unprofitable growth companies during aggressive rate hike cycles, testing this duration and profitability tilt using the Fama-French five factor model presents a highly relevant topic for future research.

5.3.3 Shifts in management styles during crises

Hypothesis 3 assumes that fund managers reduce their active risk during market crashes. Table 5 presents regression results for testing the hypothesis with model 4.

Table 5 Hypothesis 3 tested with the model 4

Variable	Coefficient	Prob.
COVID	-0.021724	0
War	-0.001836	0.3784
Constant	0.446101	0
Observations	4759	
Adjusted R-squared	0.836536	

As anticipated in the hypothesis development, measuring the exact intra-month behavioral shift during the COVID-19 panic poses a methodological challenge due to the semi-annual reporting of Active Share. However, the panel regression results successfully capture the broader structural adjustment of the portfolios. To evaluate how fund managers structurally repositioned their risk-taking behavior under market downturns, Active Share is the dependent variable and is regressed against crisis dummies. This directly tests Hypothesis 3, which posits that managers seek to minimize active risk and to have reduced portfolio deviation from benchmarks during uncertainty. Average Active Share dropped by approximately 2.17 percentage points during the COVID-19 liquidity shock.

The regression results provide strong empirical evidence for this behavioral shift. The coefficient for COVID is negative (-0.021) and highly significant at 1% level, indicating a drop in active stock picking associated with the liquidity shock. The war dummy is negative (-0.0018) and statistically insignificant (p=0.378). This shows that while managers shifted towards index lowering their active risk, they did not maintain a lower active risk throughout 2022. Hypothesis 3 is supported by empirical results for the COVID-19 shock but rejected for the full-year 2022 crisis.

Results from models 3 and 4 reveal an interesting paradox regarding managerial behavior and incentives during market shocks. While results from model 3 (Hypothesis 2a) demonstrated that a high Active Share generated positive alpha and provided downside protection during the COVID-19 crash, managers on average showed a shift away from stock picking activity during the same period.

Because of the semi-annual reporting, the outperformance was driven by pre-existing portfolios constructed before the crash, rather than active trading. This may indicate that during the COVID-19 crash, fund portfolios exhibited defensive characteristics rather than trying to maximize insurance value for investors by active trading. These drops in activeness are seen in Figures 5 and 6. This dynamic highlight conflict between the incentives of the manager and the optimal investment strategy. Theoretically, Active stock-picking is most valuable and rewarded by markets during temporary inefficiencies.

Precisely then, managers are psychologically incentivized to go towards the composition of the index and decrease the level of activeness.

Although the semi-annual reporting frequency of Active Share makes it difficult to completely isolate active trading from passive market drift, the significant decline in the metric during the COVID-19 crisis indicates a clear structural shift in portfolio compositions. Even if this decrease was driven by stock price movements, fund managers did not execute new trades to restore their previous levels of active risk. This demonstrates a conscious movement towards safety of the benchmark index.

These indications for behavioral shift are highly relevant from a regulatory perspective. ESMA (2020) has framed closet indexing as investor protection issue as investors pay higher fees for Active Management. If fund's active risk drops during a market shock investors are left paying active fees for a portfolio that is closer to the index. Also, if the insurance value of Active Management diminishes when market uncertainty peaks, investors may not be receiving the real Active Management and potential outperformance they expect to be paying for. If the theoretical insurance value of Active Management diminishes when market uncertainty peaks, the higher fees of these active funds become difficult to justify.

5.3.4 Robustness

Robustness of results was tested with different variations of dummies and interaction terms. Firstly, a longer (March to December) COVID-19 dummy and interaction term were built (Appendix 2, Table 2). Results show that the significance ($p = 0.749$) of Active Share disappear when the sample period is extended to cover the rest of the year. Additionally, period was shortened to cover March to April in 2020 (Appendix 2, Table 1). Interaction term *AS_COVID_SHORT* was statistically significant ($p = 0.021$) at 5% level. These findings strengthen the view that Active Management provides cover during acute market shock, but significance cleared away when markets recovered by the end of 2020

Consequently, shorter war dummy (March 2022 to December 2022) and interaction terms were built to cover the initial market shock to test robustness of results further (Appendix 2, Table 3). In contrast to the COVID-19 shock, the level of Active Share had no significant (P = 0.46) impact on the geopolitical crises in 2022. This highlights that the insurance value of Active Management might be limited to certain types of market shocks, such as immediate liquidity shocks.

To ensure that the positive impact of Active Share during the COVID-19 crisis was not merely driven by changing factor exposures, conditional factor loadings (SMB_COVID and HML_COVID) were added into the model (Appendix 2, Table 4). The results demonstrate that the interaction term for Active Share retained its high statistical significance (p = 0.0002) even after applying these controls. This indicates that the excess returns generated by active managers during the COVID-19 shock were the result of stock selection, rather than passive exposure to risk factors whose return profiles shifted during the crisis.

To verify that the results are not driven by fund characteristics, Model 3 was re-estimated without the fund-specific control variables (size, age, tracking error and expense ratio). The findings remain highly consistent with the baseline model: the interaction term between Active Share and the COVID-19 shock remained positive (0.026) and significant at the 1% level, while the 2022 crisis interaction remained insignificant (Appendix 2, Table 5). This confirms that the downside protection observed during the pandemic is a robust phenomenon driven by genuine stock-picking. It demonstrates that the insurance value of Active Management holds independently of the chosen control variables.

Lastly, hypothesis 3 was tested with re-adjusted model 4 (Appendix 2, Table 6) with longer COVID-19 dummy (March 2020 to December 2020). Interestingly, the extended COVID-19 variable yielded a highly significant negative coefficient (-0.027), indicating deeper drop in Active Share compared to the acute crash. This suggest that shift towards closet indexing sustained throughout the 2020 pandemic year as macroeconomic uncertainty remained. Short-term event window could not be reliably tested for the 2022 geopolitical crisis as initial shock was short and therefore hard to capture in the premises of semi-annual reporting frequency of Active Share.

Excess returns, tracking error and expense ratios were winsorized at the 1st and 99th percentiles prior to the regressions. This ensures that performance is real phenomenon within the Nordic mutual fund market, rather than driven by extreme outliers or data errors.

5.3.5 Implications for investor

Figure 11 demonstrates the development of high Active Share (over 60%) and passive strategies over the sample period (December 2016 to December 2024).

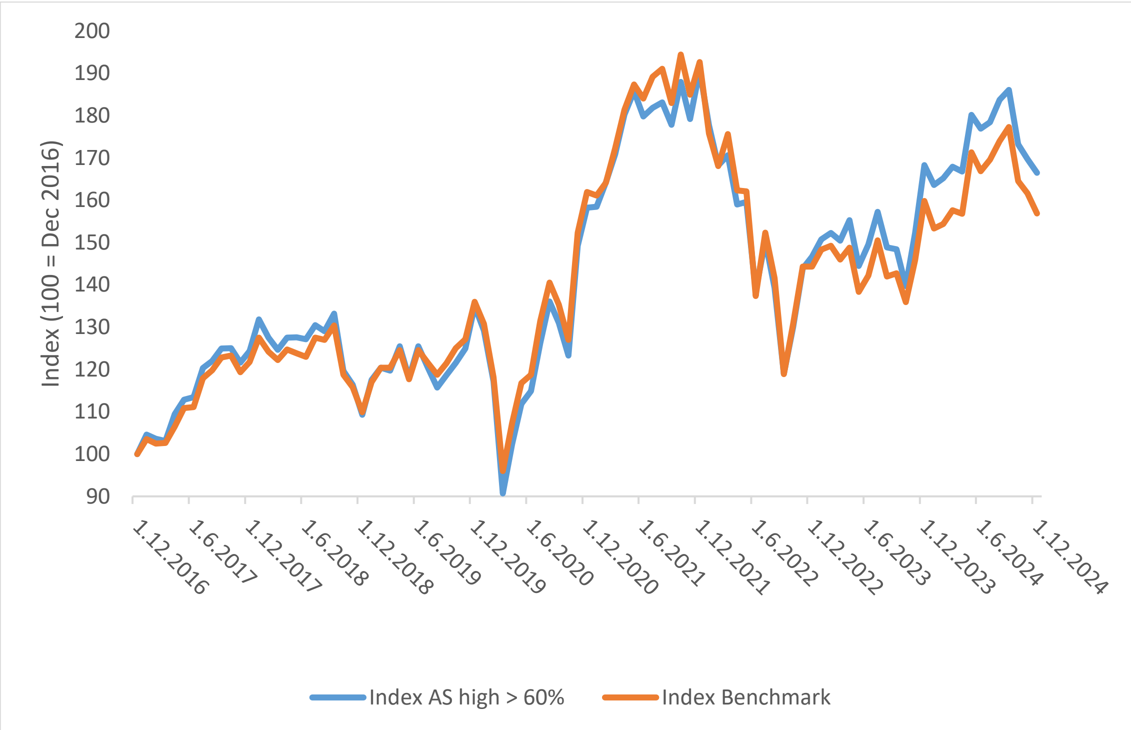

Figure 11 The figure illustrates the cumulative growth of a 100 € investment in high Active Share funds (blue) and the market benchmark (orange), indexed to 100 in December 2016.) The benchmark represents the average monthly return of all fund-specific benchmarks in the sample

For long-term retail investors, Nordic low-cost passive index funds remain the most efficient investing strategy. Even though high Active Share matched the benchmark cumulative net returns over the eight-year period (Figure 11), regression analysis reveals that this performance is due to structural factor exposures rather than superior stock-picking skills. Paying high management and transaction fees appears to be suboptimal, as Active Management fails to produce significant risk-adjusted alpha during normal market conditions or during prolonged macroeconomic shifts like the 2022 crisis. High Active Share does offer insurance value during acute liquidity shocks, such as the COVID-19 crash. Benefitting from this is difficult as managers often reduce their career risk by reducing active risk and moving towards closet indexing, precisely when the protection is needed the most.

Figure 7 reveals that the majority of active Nordic funds fall into Factor Bets category (Low Active Share, high tracking error). For investor, this presents a risk. They may be paying for active fees for portfolios that do not offer unique stock-picking. Instead, these funds achieve their tracking error through style factors or sector tilts. This may indicate that many Nordic investors are exposed to closet indexing in terms of fund holdings, even if the fund's volatility appears high. These findings imply that Nordic investors must look beyond the active label.

6 Limitations of the study

A primary limitation of this study is reliance on semi-annual portfolio holdings data to calculate Active Share. Because holdings are reported semi-annually, the metric provides a static picture of fund activeness. It cannot capture the intra-month trading or precise behavioral shifts during the market shocks.

One limitation of this study relates to the use of European Carhart-four factor data, retrieved from Kenneth French's data library. The European markets are weighted towards major markets such as the UK, France, Germany and Switzerland. Their sector composition differs from universe of Nordic fund managers. It is possible that the factor loadings and the resulting alpha partially capture geographical tracking error rather than the manager's skill or local factor exposure. Constructing localized Nordic risk factors would provide more results on performance. However, due to data availability and the data processing required, building regional factors falls outside the scope of this thesis.

The data for theoretical market indices was unavailable actual index funds were used as benchmarks. While this is realistic from investor's perspective as theoretical indices cannot be invested in, real index funds have slight tracking error, cash buffers and management fees. Therefore, they do not perfectly replicate the market returns. As results this may cause minor distortions in Active Share and Tracking Error calculations.

The precise definition of crisis periods involves some degree of subjectivity. COVID-19 was a sudden event and shock, whereas the 2022 crisis was a prolonged macroeconomic shift. The robustness checks tested different timeframes; broad economic shifts do not have clear start or end dates. Therefore, the exact timing chosen for dummy variables might slightly affect the returns.

Studying only two crisis periods limits the generalizability of the results. Because the study analyses just two events, the findings cannot be applied to all past and future crises. However, this limitation is balanced by the highly contrasting nature of the two crises.

The COVID-19 crash was a sudden, fear-driven liquidity shock, while the 2022 crisis was a prolonged inflationary period. Even if these results do not apply to every bear market, comparing these two opposite crises provides valuable insights into how active managers perform under different market conditions.

7 Summary of the results

This chapter summarizes the main empirical findings of the study and evaluates them against the hypotheses. The main objective of this thesis was to investigate whether active portfolio management, measured by Active Share, provides economic value and downside protection in the Nordic equity markets during normal market conditions and crisis periods (The COVID-19 crash and the 2022 geopolitical crisis).

H1 (Baseline performance): Rejected. The first hypothesis posits that high Active Share funds generate positive net alpha during normal market conditions. The baseline regression model did not provide evidence that the higher level of Active Management translates into outperformance net of fees during the full sample period.

H2A: (Shock Period-COVID-19): Supported. The hypothesis, assuming that Active Share provides downside protection during an acute COVID-19 market shock, is supported. The interaction term between Active Share and the COVID-19 crash was positive and highly significant, demonstrating that active managers were able to generate risk-adjusted alpha during the crisis. However, this outperformance is likely due to the resilience of high-conviction portfolios constructed prior to the crash rather than intra-month trading.

H2B (Prolonged crisis – Ukraine War): Rejected. In contrast to the COVID-19 shock, the hypothesis that Active Management adds value during a prolonged macroeconomic crisis is rejected. The interaction term for the 2022 geopolitical crisis was statistically insignificant, suggesting that systematic factors and duration penalties overwhelmed individual stock-picking skills.

H3 (Behavioral shift): Partially supported. The third hypothesis assumes that managers reduce active risk during crises. This was supported during the COVID-19 crash, where average Active Share dropped significantly, indicating a shift towards closet indexing. The effect persisted through initial crash and the extended period (March to December). This shift was not statistically significant during the 2022 crisis.

8 Conclusion

Under normal market conditions, high Active Share does not generate significant risk-adjusted alpha in the Nordic market once fees and systematic risk factors are accounted for. Consequently, a low-cost passive index fund remains the most efficient core strategy for retail investors. However, during a sudden fear and liquidity shock, such as the COVID-19 crash, active stock-picking acted as a critical shock absorber. Although high Active Share funds suffered absolute losses due to their structural exposure to small-cap stocks (the SMB factor), managerial skill generated positive risk-adjusted alpha, softening the drop. During the prolonged macroeconomic and interest rate crisis of 2022, Active Management failed to provide similar protection, as broad systematic factors overwhelmed individual stock-picking. The data reveal a behavioral shift: the degree of active risk exhibited by managers declined significantly during the COVID-19 panic. This highlights a conflict, as it disadvantages investors who pay a premium for active downside protection precisely when it is most needed.

This thesis makes several key contributions to the existing academic literature. Firstly, it extends the Active Share framework of Cremers and Petajisto (2009) to the more concentrated Nordic equity market. Second, it expands Glode's (2011) insurance hypothesis by demonstrating that the protective value of Active Management is conditional on the nature of the specific crisis. Lastly, this study challenges the findings of Pástor and Vorsatz (2021); by categorizing funds based on their degree of activeness, the results suggest that truly active managers were capable of generating alpha during the acute phase of the COVID-19 pandemic, unlike closet-indexers.

For future research, applying the Fama-French five factor model would be interesting, particularly analysing the 2022 macroeconomic crisis. The rapid interest rate hikes during this period penalized unprofitable, long-duration growth companies. Using the profitability and investment factors would clarify whether the lack of risk-adjusted outperformance by active funds in 2022 was driven by poor stock-picking or by a structural portfolio overweight in unprofitable long duration growth equities.

9 List of references

Airaksinen, M., Berglund, T., & von Weymarn, T. (2014). Corporate governance in Finland. In P. Lekvall (Ed.), The Nordic corporate governance model (pp. 123–162). SNS Förlag.

Anadu, K., Kruttli, M., McCabe, P., & Osambela, E. (2020). The shift from active to passive investing: Potential risks to financial stability? *Financial Analysts Journal, 76(4), 23–39.* https://dx.doi.org/10.2139/ssrn.3244467

Andersen, T. M., Holmström, B., Honkapohja, S., Korkman, S., Söderström, H. T., & Vartiainen, J. (2007). The Nordic model: Embracing globalization and sharing risks. Taloustieto Oy.

Berk, J. B., & Green, R. C. (2004). Mutual fund flows and performance in rational markets. *Journal of Political Economy, 112(6), 1269–1295*. https://doi.org/10.1086/424739

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, *52*(1), 57–82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x

Central Bank of Ireland. (2019, July 18). *Thematic review of closet indexing* [Industry letter]. https://www.centralbank.ie/news/article/press-release-thematic-review-of-closet-indexing-18-july-2017

Cremers, M., & Pareek, A. (2016). Patient capital outperformance: The investment skill of high Active Share managers who trade infrequently. *Journal of Financial Economics*, *122*(2), 288–306. https://doi.org/10.1016/j.jfineco.2016.08.003

Cremers, K. J. M., & Petajisto, A. (2009). How active is your fund manager? A new measure that predicts performance. *The Review of Financial Studies*, *22*(9), 3329–3365. https://doi.org/10.1093/rfs/hhp057

Cremers, M., Ferreira, M. A., Matos, P., & Starks, L. (2016). Indexing and active fund management: International evidence. *Journal of Financial Economics*, *120*(3), 539–560. https://doi.org/10.1016/j.jfineco.2016.02.008

Danske Invest. (2025). *Prospectus: Investeringsforeningen Danske Invest Index*. Danske Invest Management A/S.

Directive 2009/65/EC of the European Parliament and of the Council of 13 July 2009 on the coordination of laws, regulations and administrative provisions relating to undertakings for collective investment in transferable securities (UCITS). (2009). *Official Journal* *of the European Union*, *L 302*, 32–96. Retrieved from: http://data.europa.eu/eli/dir/2009/65/oj

EFAMA. (2025). *Market Insights Issue #21: The SFDR fund market – Latest market trends and the upcoming SFDR review*. European Fund and Asset Management Association. Retrieved from: https://www.efama.org/sites/default/files/files/market-insights-21-the-sfdr-fund-market.pdf

Ellis, C. D. (2014). The rise and fall of performance investing. *Financial Analysts Journal*, *70*(4), 14–23. https://doi.org/10.2469/faj.v70.n4.4

European Commission. (2025). *Sustainability-related disclosure in the financial services sector*. https://finance.ec.europa.eu/sustainable-finance/disclosures/sustainability-related-disclosure-financial-services-sector_en

European Securities and Markets Authority. (2020). *Costs and performance of potential closet index funds* (ESMA Report on Trends, Risks and Vulnerabilities No. 2, 2020). Retrieved from: https://www.esma.europa.eu/sites/default/files/trv_2020_2-costs_and_performance_of_potential_closet_index_funds.pdf

Evans, R. B. (2010). Mutual fund incubation. The Journal of Finance, 65(4), 1581–1611. https://doi.org/10.1111/j.1540-6261.2010.01579.x

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, *25*(2), 383–417. https://doi.org/10.2307/2325486

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1), 3–56. https://doi.org/10.1016/0304-405X(93)90023-5

Fama, E. F., & French, K. R. (2010). Luck versus skill in the cross-section of mutual fund returns. *The Journal of Finance*, *65*(5), 1915–1947. https://doi.org/10.1111/j.1540-6261.2010.01598.x

Financial Conduct Authority. (2018). *Closet trackers*. (2018, March 14) https://www.fca.org.uk/firms/authorised-and-recognised-funds/closet-trackers

Flam, H., & Vestman, R. (2017). Swedish Equity Mutual Funds 1993-2013: Performance, Persistence and Presence of Skill https://dx.doi.org/10.2139/ssrn.3082073

Frazzini, A., Friedman, J., & Pomorski, M. (2016). Deactivating Active Share. *Financial Analysts Journal*, *72*(3), 14–21. https://doi.org/10.2469/faj.v72.n2.2

Fuller, R. J., Han, B., & Tung, Y. (2010). Thinking about indices and "passive" versus Active Management. *The Journal of Portfolio Management*, *36*(4), 35–47. https://doi.org/10.3905/jpm.2010.36.4.035

Gagnon, J., Raskin, M., Remache, J., & Sack, B. (2011). The Financial Market Effects of the Federal Reserve's Large-Scale Asset Purchases. *International Journal of Central Banking*, 7(1), 3-43.

Glode, V. (2011). Why mutual funds "underperform". *The Journal of Finance 66(2) (2011) 563-600.* https://doi.org/10.1016/j.jfineco.2010.10.008

Gonzalez Ehnes, R., Noman, A., & Rahman, M. (2024). Tracking ability of iShares country ETFs during the Covid-19 Pandemic. *Journal of Finance Issues*, *22*(1), 1–13 https://doi.org/10.58886/jfi.v22i1.6796

Grossman, S. J., & Stiglitz, J. E. (1980). On the impossibility of informationally efficient markets. *The American Economic Review*, *70*(3), 393–408. https://doi.org/10.7916/D8765R99

Gruber, M. J. (1996). Another puzzle: The growth of actively managed mutual funds. *The Journal of Finance*, *51*(3), 783–810. https://doi.org/10.1111/j.1540-6261.1996.tb02707.x

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, 48(1), 65–91. https://doi.org/10.1111/j.1540-6261.1993.tb04702.x

Jensen, M. C. (1968). The performance of mutual funds in the period 1945–1964. *The Journal of Finance*, *23*(2), 389–416. https://doi.org/10.1111/j.1540-6261.1968.tb00815.x

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica, 47(2), 263–292.* https://doi.org/10.2307/1914185

Kjørven, M. E. (2018). *Closet index funds and retail investor protection: A Scandinavian perspective* [Working paper]. University of Oslo.

KLP. (2024). Årsrapport 2023 - KLP-fondene. Kommunal Landspensjonskasse. https://www.klp.no/om-klp/finans-og-ir/rapporter-og-presentasjoner

Kosowski, R. (2011). Do mutual funds perform when it matters most to investors? US mutual fund performance and risk in recessions and expansions. *The Quarterly Journal of Finance 1 (03), 607-664*. http://dx.doi.org/10.2139/ssrn.926971

Laaksonen, V. (2023). *Active Share and fund performance: Evidence from Finland* [Master's thesis, University of Vaasa]. Osuva.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The Review of Economics and Statistics*, *47*(1), 13–37. https://doi.org/10.2307/1924119

Lo, A. W. (2004). The adaptive markets hypothesis: Market efficiency from an evolutionary perspective. *The Journal of Portfolio Management*, *30*(5), 15–29. https://doi.org/10.3905/jpm.2004.442611

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance, 7(1), 77–91.* https://doi.org/10.1111/j.1540-6261.1952.tb01525.x

Modigliani, F., & Cohn, R. A. (1979). Inflation, rational valuation and the market. *Financial Analysts Journal*, *35*(2), 24–44. https://doi.org/10.2469/faj.v35.n2.24

Mossin, J. (1966). Equilibrium in a capital asset market. *Econometrica, 34(4), 768–783.* https://doi.org/10.2307/1910098

MSCI. (2026**).** *MSCI Nordic Countries Index (EUR) Factsheet*

Pástor, L., Stambaugh, R. F., & Taylor, L. A. (2015). Scale and skill in Active Management. *Journal of Financial Economics*, *116*(1), 23–45. https://doi.org/10.1016/j.jfineco.2014.11.008

Pástor, L., & Vorsatz, M. B. (2021). Mutual fund performance and flows during the COVID-19 crisis. *The Review of Asset Pricing Studies, Society for Financial Studies, vol. 10(4), pages 791-833, https://dx.doi.org/10.2139/ssrn.3648302*

Petajisto, A. (2013). Active Share and mutual fund performance. *Financial Analysts Journal*, *69*(4), 73–93. https://doi.org/10.2469/faj.v69.n4.7

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, *19*(3), 425–442. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x

Sharpe, W. F. (1966). Mutual fund performance. *The Journal of Business*, *39*(1), 119–138. http://dx.doi.org/10.1086/294846

Sharpe, W. F. (1991). The arithmetic of Active Management. *Financial Analysts Journal*, *47*(1), 7–9. https://doi.org/10.2469/faj.v47.n1.7

Shiller, R. J. (2003). From efficient markets theory to behavioral finance. *Journal of Economic Perspectives*, *17*(1), 83–104. https://doi.org/10.1257/089533003321164967

Shleifer, A., & Vishny, R. W. (1997). The limits of arbitrage. *The Journal of Finance*, *52*(1), 35–55. https://doi.org/10.1111/j.1540-6261.1997.tb03807.x

Thaler, R. H. (1987). Anomalies: The January effect. *The Journal of Economic Perspectives*, *1*(1), 197–201. https://doi.org/10.1257/jep.1.1.197

Thomsen, S. (2016). The Nordic corporate governance model. *Management and Organization Review*, *12*(1), 189–204. https://doi.org/10.1017/mor.2015.55

Tobin, J. (1958). Liquidity preference as behavior towards risk. *The Review of Economic Studies, 25(2), 65–86.* https://doi.org/10.2307/2296205

10 Appendix 1 List of funds

STOREBRAND NORGE FUND	Norway
PARETO AKSJE NORGE I	Norway
DANSKE INVEST NOR AKS IN II	Norway
FONDSFINANS NORGE - A	Norway
HOLBERG NORGE A	Norway
DNB NORGE-C NOK ACC	Norway
HANDELSBANKEN NORGE - A1 NOK	Norway
NORDEA AVKASTNING	Norway
NORDEA KAPITAL	Norway
STOREBRAND VERDI FUND	Norway
KAPF.NIE DANSKE FOKUSAKT -KL	Denmark
NORDEA NORGE VERDI	Norway
ARCTIC NORW VALUE CR-B NOK	Norway
ODIN NORGE-CNOK	Norway
EIKA NORGE-A	Norway
ARCTIC-NORWEGIAN EQUITIES-I	Norway
ALFRED BERG NORGE-R NOK	Norway
ALFRED BERG GAMBAK - R NOK	Norway
LANNEBO SVERIGE	Sweden
PRIORNILSSON SVERIGE AKTIV-A	Sweden
NORDEA SWEDISH STARS	Sweden
D&G AKTIEFOND	Sweden
NORDEA ALLEMANSFOND ALFA	Sweden
KERNE INVEST DANSKE AKTIER	Denmark
SWEDBANK ROBUR SVER FD MEGA	Sweden
CARNEGIE SVERIGEFOND-A	Sweden
SWEDBANK ROBUR SVERIGE-ASEK	Sweden
AMF AKTIEFOND SVERIGE	Sweden
PARETO SVERIGE-A	Sweden
STOREBRAND SVERIGE- A SEK	Sweden
SELIGSON & CO FINLAND INDX-A	Finland
HANDELSBANKEN SV TEMA-A1 SEK	Sweden
AKTIA CAPITAL-A	Finland
DANSKE INV-FINNISH-EQT-GROWT	Finland
LANSFORSAKRINGR SVRG VISION	Sweden
NORDEA PRO FINLAND FD-GROWTH	Finland
EQ SUOMI-1 K	Finland
SEB SVERIGEFOND	Sweden
AKTIA FINLAND VALUE-A	Finland

SAASTOPANKKI KOTIMAA-A	Finland
SEB-FINLANDIA OPT LOW CARB-A	Finland
BLS INVEST DANSKE AKTIER-A	Denmark
S-BANK FENNO EQUITY	Finland
DANSKE INV FIN DVD PLUS FUND	Finland
ELITE ALF BERG SUOMI FOKUS-A	Finland
SYDINVEST DANMARK FUND	Denmark
LAN & SPAR INVEST DANSKE AKT	Denmark
SPARINVEST DANSKE AKTIER KL	Denmark
C WORLDWIDE DANMARK KL	Denmark
NYKREDIT INVEST DANSKE AKT A	Denmark
JYSKE INVEST DANSKE AKTIER K	Denmark
BI DANSKE AKTIER AKK. KL	Denmark
SEBINVEST DANISH EQUITIES FD	Denmark
EVLI FINLAND SELECT-A	Finland
ODIN FINLAND C	Norway
DANSKE INV-FIN-INSTIT-EQT-G	Finland
SKANDIA SVERIGE	Sweden
OP-FOCUS-A	Finland
OP-DELTA-A	Finland
FF SEBINVEST II DANSKE AKTIE	Denmark
LAN&SPAR RATIONEL INV DANMAR	Denmark
DANSKE INVEST SVERIGE	Sweden

Benchmark indices:

Nordea Suomi Indeksi, Finland

Länsförsäkringar Sverige Indexnära, Sweden

KLP AksjeNorge Indeks, Norway

Bank Invest Danske Aktier Indeks, Denmark

11 Appendix 2 Robustness checks

Table 1 Robustness check COVID Short dummy. Standard errors are reported in parentheses. Significance levels are denoted by * (1%), ** (5%), and * (10%)**

Variable	Robustness check (Short COVID)
C (intercept)	-0.035
	(0.0268)
Active Share (t-1)	0.002
	(0.0043)
Market Premium	0.9097***
	(0.0189)
SMB (Size-factor)	0.1484***
	(0.0437)
HML (Value factor)	-0.027
	(0.0288)
MOM (Momentum)	-0.010
	(0.0368)
Tracking Error (t-1)	-0.027
	(0.0538)
Log Size (t-1)	-0.002
	(0.0016)
Expense Ratio (t-1)	-0.003
	(0.0020)
Age (t-1)	0.0099*
	(0.0056)
D_COVID_SHORT	-0.005
	(0.0042)
AS_COVID_SHORT	0.0224**
	(0.0095)
Observations (N)	4405
Adjusted R-squared	0.903304
Fund specific effects (FE)	Yes

Table 2 Robustness check COVID Long standard errors are reported in parentheses. Significance levels are denoted by * (1%), ** (5%), and * (10%)**

Variable	Robustness check (Long COVID)
C (intercept)	-0.036
	(0.0269)
Active Share (t-1)	0.003
	(0.0042)
Market Premium	0.9077***
	(0.0184)
SMB (Size-factor)	0.1402***
	(0.0463)
HML (Value factor)	-0.029
	(0.0287)
MOM (Momentum)	-0.010
	(0.0382)
Tracking Error (t-1)	-0.029
	(0.0540)
Log Size (t-1)	-0.002
	(0.0016)
Expense Ratio (t-1)	-0.003
	(0.0021)
Age (t-1)	0.0098*
	(0.0057)
D_COVID_LONG	0.001
	(0.0023)
AS_COVID_LONG	0.003
	(0.0100)
Observations (N)	4405
Adjusted R-squared	0.90326
Fund specific effects (FE)	Yes

Table 3 Robustness check War short standard errors are reported in parentheses. Significance levels are denoted by * (1%), ** (5%), and * (10%)**

Variable	Robustness check war short
Intercept	-0.0394
	(0.0269)
Active Share lagged	0.0017
	(0.0042)
Market Premium	0.9062***
	(0.0180)
SMB (Size factor)	0.1556***
	(0.0449)
HML (Value factor)	-0.0159
	(0.0263)
MOM (Momentum)	-0.0082
	(0.0378)
Tracking Error lagged	-0.0114
	(0.0543)
Log Size lagged	-0.0018
	(0.0016)
Expense Ratio lagged	-0.0027
	(0.0020)
Age lagged	0.0097*
	(0.0057)
COVID-19	-0.0021
	(0.0030)
Active Share*COVID-19	0.0234***
	(0.0061)
War short	-0.0023
	(0.0070)
Active Share*War short	-0.0120
	(0.0164)
Observations (N)	4405

Adjusted R-squared	0.904

Table 4 Factors x COVID standard errors are reported in parentheses. Significance levels are denoted by * (1%), ** (5%), and * (10%)**

Variable	SMB HML_COVID
C (intercept)	-0.0376
	(0.0270)
Active Share (t-1)	0.0021
	(0.0042)
Market Premium	0.9069***
	(0.0204)
SMB	0.1571***
	(0.0468)
HML	-0.0251
	(0.0317)
MOM (Momentum)	-0.014
	(0.0369)
Tracking Error (t-1)	-0.0202
	(0.0540)
Log Size (t-1)	-0.0019
	(0.0016)
Expense Ratio (t-1)	-0.0027
	(0.0020)
Age (t-1)	0.0096*
	(0.0057)
SMB (Size-factor)_Covid	-0.065
	(0.0636)
HML (Value factor)_Covid	0.0626
	(0.0466)
COVID-19 Dummy	0.0006
	(0.0021)
Active Share X COVID	0.0237***
	(0.006097)
Observations (N)	4405
Adjusted R-squared	0.905
Fund specific effects (FE)	Yes

Table 5 No controls included robustness check standard errors are reported in parentheses. Significance levels are denoted by * (1%), ** (5%), and * (10%)**

Variable	Robustness check no controls
C (intercept)	0.000
	(0.0017)
Active Share (t-1)	0.001
	(0.0035)
Market Premium	0.9042***
	(0.0177)
SMB (Size-factor)	0.1530***
	(0.0436)
HML (Value factor)	-0.010
	(0.0256)
MOM (Momentum)	-0.008
	(0.0385)
D_WAR	0.001
	(0.0040)
AS_WAR	-0.0030
	(0.0076)
D_COVID	-0.002
	(0.0037)
AS_COVID	0.0262***
	(0.0072)
Observations (N)	4754
Adjusted R-squared	0.901
Fund specific effects (FE)	Yes

Table 6 model 4 Long Covid

Variable	Coefficient	Prob.
Covid long	-0.027393	0
Constant	0.44782	0
Observations	4759	
Adjusted R-squared	0.84043	