WHEN ACTIVE PAYS OFF

THE ROLE OF ACTIVE SHARE IN TURBULENT MARKETS

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Abstract:

This paper examines the role of Active Share in Swedish equity mutual funds across varying market conditions. Using quarterly holdings and daily returns from the end of 2018 to the end of 2024, we compute Active Share for all-equity mutual funds domiciled in Sweden that invest in Europe and match them to appropriate benchmarks. We find no consistent relationship between Active Share and excess return throughout our sample period. However, during periods of elevated uncertainty, most notably the COVID-19 crisis, funds with high Active Share significantly outperform their benchmarks, while no such evidence exists for funds with lower Active Share. These results suggest that the relevance of Active Share is context-dependent and particularly significant in turbulent markets. Our findings imply that investors and fund managers should consider Active Share a meaningful indicator primarily during periods of heightened uncertainty.

Keywords:

Active Share, Fund Management, Market Uncertainty, Excess Return, Swedish Equity Funds

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I. Introduction

Periods of heightened market volatility and uncertainty, such as the COVID-19 outbreak, Russia's invasion of Ukraine, and most recently, proposed U.S. tariffs by the Trump administration, may offer the most favourable conditions for actively managed funds to exploit mispriced securities. In contrast, passive strategies remain tied to their underlying benchmarks. The pros and cons of active and passive investing represent one of the most central debates in finance. The core question is whether skilled fund managers can consistently generate returns that justify their fees. However, several prominent researchers consistently show, through empirical evidence, that active funds underperform passive alternatives net of fees (Jensen, 1968; Fama and French, 2010; Berk and van Binsbergen, 2015). Carhart (1997, p. 57) explicitly states, "The results do not support the existence of skilled or informed mutual fund portfolio managers."

While the empirical evidence supports that active funds underperform passive benchmarks on average, most studies fail to distinguish between those legally classified as actively managed and truly active funds. To address this, Cremers and Petajisto (2009) introduce a new metric, Active Share, which measures the percentage of a fund's holdings that deviate from its benchmark index, ranging from 0 to 100%. One practical application of the metric is to identify which funds are truly active. By applying Active Share to U.S mutual funds between 1980 and 2003, the study finds that the most active funds outperform their benchmark indexes after fees on average by 1.15% per year, while the least active funds tend to generate lower returns than their benchmarks.

The Swedish mutual fund market has several distinct features, making it compelling to examine whether previous findings on Active Share hold in a different institutional context. Sweden exhibits high retail engagement in the financial market, partly driven by the pension system, which allocates retirement savings into mutual funds (Swedish Investment Fund Association, 2024). In addition, most Swedish mutual funds are regulated under the UCITS Act, which imposes the 5/10/40 rule[1] that governs portfolio diversification (European Commission 2016; Swedish Financial Supervisory Authority 2024). Lastly, Sweden has one of the highest levels of closet indexers, funds with an Active Share below 60%, among the 32 countries, according to a study by Cremers, Ferreira, Matos and Starks (2016).

Hypothetically, periods of high volatility and uncertainty may offer investors favourable conditions to exploit temporary market mispricings. Unlike less active managers, these environments would benefit the truly active managers, who are more likely to deviate from their benchmark to act on perceived mispricing. Active Share is a suitable metric for capturing these differences in managerial behaviour, as it reflects the extent to which a manager deviates from the benchmark and thus indicates the level of independent stock picking. COVID-19 is particularly interesting to examine, as it represents a rapid escalation of uncertainty that affects all sectors to some extent, making it an ideal setting for investigating managerial skills.

[1]The 5/10/40 rule stipulates that one holding cannot exceed 10% of the fund, and the five largest holdings together cannot exceed 40% of the fund.

Focusing on the Swedish fund market and examining performance in volatile markets, particularly during COVID-19, this study addresses two main research questions: (1) Is Active Share significantly associated with excess return in Sweden? (2) Is Active Share significantly associated with excess return during heightened market uncertainty (COVID-19)?

To address these questions, we construct a comprehensive dataset of actively managed Swedish equity mutual funds and 11 benchmark indices, with detailed holdings and returns from Q4 2018 to Q4 2024. We compute Active Share for each fund relative to its benchmark and track fund performance using excess returns over the assigned benchmark. We define the COVID-19 crisis window from 27 February to 7 May 2020, when the EURO STOXX 50 volatility index exceeds 30, and apply panel regression models with standard asset pricing controls. We also examine broader uncertainty periods using the volatility index as a proxy.

Our key findings reveal a nuanced role for Active Share. Throughout our full sample period, higher Active Share does not explain superior performance. This aligns with recent scepticism about Active Share's predictability. However, during the COVID-19 crisis, the relationship changes. Funds with an Active Share above 80% significantly outperform, generating an average daily excess return of 0.13%. This effect, if annualised, corresponds to double-digit outperformance. In contrast, funds with an average Active Share below 60% underperform their benchmark during the broader uncertain period. These results suggest that highly active funds navigate turbulent markets more effectively by deviating from the benchmark constraints and capitalising on mispricings.

Importantly, we do not claim to resolve the central debate in finance, whether active or passive investing is superior. Instead, we show that the value of Active Share is context-dependent. Simply holding a highly active portfolio does not guarantee superior returns in calm markets; however, it appears valuable in turbulent markets. This thesis thus makes two main contributions to the literature. First, it provides an in-depth analysis of Active Share and performance in the overlooked Swedish mutual fund market. Second, it offers novel insights on how Active Share interacts under extreme market conditions, mainly the COVID-19 pandemic, an event not studied in prior Active Share research. By addressing these gaps, we enhance the understanding of Active Share as a predictor of fund performance and highlight the conditions under which active management truly proves its worth. The results have practical implications for investors and fund managers: truly active management can be a source of resilience and alpha in turbulent times, even if its advantages are less pronounced in normal times. Our study thus aligns with and expands upon the Active Share literature, showing whether Active Share matters, and when it matters the most.

II. Literature Review and Theoretical Background

A. Active Share as an Indicator of Active Management and Performance

Among actively managed funds, a core challenge is to distinguish between managers who independently select stocks they perceive as undervalued and those who mimic their portfolio closely to their benchmark to reduce the risk of underperforming their benchmarks. An investor who pays a fee for active management, but receives a portfolio that merely replicates the benchmark, does not get what they pay for. To combat this problem, various metrics are used to measure how active a fund is, most commonly Tracking Error, the standard deviation of return differences between the fund and its benchmark.

However, Tracking Error can be misleading as it is sensitive to factor bets and does not fully capture active stock picking. For example, a fund with a high level of stock picking, but broad diversification, may have low Tracking Error. In contrast, a fund with large factor bets may show high Tracking Error, although it resembles the benchmark. To address this problem, Cremers and Petajisto (2009) introduce Active Share, a holdings-based metric that measures the percentage of a fund's holdings that deviate from its benchmark. Intuitively, a fund with zero Active Share exactly replicates the benchmark, with identical holdings and weights. The authors argue that Active Share offers two main contributions. First, Active Share indicates potential for outperformance, since mathematically, the only way to outperform is by deviating from it. Second, combining Active Share and Tracking Error allows for a detailed classification of the investment strategy a fund applies, although the study highlights that Active Share is a good metric by itself. The presented framework, as seen in Figure 1, distinguishes five investment strategies, separating factor timing and stock selection, which is not possible using Tracking Error alone. Beyond being intuitive and improving the classifications of fund strategies, the study also suggests that Active Share is associated with benchmark-adjusted excess returns. Their study examines mutual funds in the U.S. between 1980 and 2003 and finds that funds in the highest Active Share quintile significantly outperformed with an average of 1.15% per year, even while adjusting for Carhart factors. Meanwhile, funds with the lowest Active Share significantly underperform. In addition, the study presents evidence that outperformance among high Active Share funds persists over time. Their results expand the debate of active versus passive investments by highlighting that not all active funds are equal in practice.

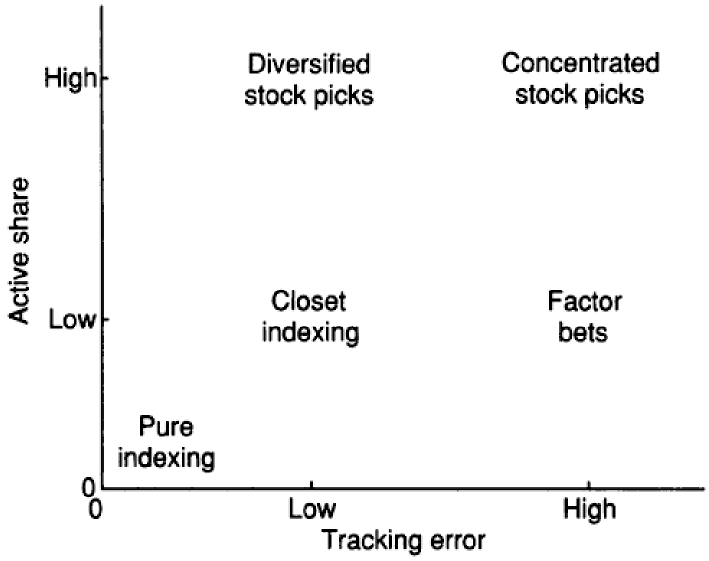


Figure 1. The Active Management Landscape.
This figure illustrates the joint distribution of Active Share and Tracking Error across fund strategies. Funds in the bottom-left engage in pure indexing, while those with low Tracking Error but high Active Share are typically diversified stock pickers. Closet indexers mimic their benchmark closely despite appearing active. Funds with high Tracking Error but low Active Share often engage in factor bets, and those high on both dimensions represent concentrated stock pickers. The framework highlights that Active Share and Tracking Error capture distinct dimensions of active management. This figure is reproduced from Cremers and Petajisto (2009).

While Active Share offers a new perspective on activeness focused on stock selection, its relationship to excess return is challenged in subsequent research. Frazzini, Friedman and Pomorski (2016), using the same data set as Cremers and Petajisto (2009), argue that Active Share does not predict excess return because it correlates with its benchmark returns. The study finds no evidence of return differences between high and low Active Share funds when comparing funds within the same bucket. Thus, the authors do not support Active Share as a metric for choosing funds, although they highlight its potential use in evaluating fees. In response, Petajisto (2015) defends the predictive power of Active Share, while agreeing that its levels vary across benchmarks. He highlights that most of the critique is already addressed in the original paper. Moreover, he challenges the benchmark adjustments method used by Frazzini et al., which he claims overweights categories with few funds, potentially skewing the results. Petajisto re-estimates performance with what he considers a more appropriate adjustment and finds that high Active Share remains positively associated with excess return.

More recent research explores the role of trading behaviour in this relationship. Cremers and Pareek (2016) find that high Active Share funds with long holding periods, defined as over two years, on average outperform by 2% per year. In contrast, high Active Share funds that trade frequently tend to underperform, emphasising the importance of holding investments over time. However, trading infrequently by itself does not lead to outperformance, as funds with low Active Share and low turnover still underperform. These findings imply that both high Active Share and long-term orientation are necessary for outperformance.

In a global context, Cremers et al. (2016) examine how competition from index funds affects activeness and pricing. They find that in markets with increased competition from index funds, actively managed funds tend to increase their activeness and reduce fees. Among the 32 countries studied, Sweden has the second-highest share of closet indexers, implying that a large proportion of active funds exhibit a low Active Share.

As presented, prominent research on Active Share in non-U.S. markets remains limited. Although Cremers et al. (2016) examined an international sample, their focus is not on the relationship between Active Share and excess return. As a result, there is little evidence of how effectively Active Share explains performance in countries outside of the U.S. By examining Active Share in a Swedish context, we aim to test whether the findings based on U.S. data hold in the Swedish market, with different regulations and institutional characteristics.

B. Active Management in Volatile Markets

A common argument in the debate between active and passive management is that active funds may add value during turbulent periods. During volatile markets, mispricings tend to happen more frequently, creating opportunities for skilled managers to exploit inefficiencies or avoid overpriced assets. Crises often affect sectors differently, and unlike passive funds that remain tied to an index, active managers can shift sector exposures or tilt portfolios away from the worst-hit areas. This flexibility can benefit active investors during downturns.

Partly supporting this perspective, Kacperczyk, Van Nieuwerburgh and Veldkamp (2014) find that certain managers systematically improve performance in recessions by reallocating attention towards macroeconomic risks. Building on this, Kacperczyk, Van Nieuwerburgh and Veldkamp (2016) argue that managers rationally shift attention between firm-specific and aggregate signals depending on the economic environment, with recessions favouring a macro focus. Although these findings do not apply to every active manager, they suggest that skill and adaptability allow active managers to outperform in turbulent times.

However, more recent empirical evidence suggests otherwise. Pastor and Vorsatz (2020), in their analysis of U.S. equity mutual funds during the COVID-19 crisis, find that 74% of active funds underperform the S&P 500 with an average excess return of -5.6% relative to the index over a ten-week crisis window, or -29.1% annualised. This finding aligns with broader research showing that, on average, funds fail to deliver alpha after fees (Fama and French, 2010; Carhart, 1997).

Although these findings may seem contradictory, that is not necessarily the case. Kacperczyk et al. (2014, 2016) show that there are skilled fund managers who can yield alpha in recessions, while Pastor and Vorsatz argue that fund managers, on average, fail to deliver alpha during COVID-19. Together, these findings highlight a central tension in the literature: while theory predicts that skilled managers should outperform in periods of uncertainty, real performance often falls short.

However, it remains an open question how Active Share interacts with crisis performance. Do funds with higher Active Share fare better or worse during the COVID-19 crisis? Our study contributes to the literature by addressing this question, examining whether Active Share, as a measure of activeness, explains fund performance during periods of elevated uncertainty in a different institutional context.

III. Methodology

Our research design follows a quantitative empirical approach similar in spirit to earlier Active Share studies (e.g. Cremers and Petajisto 2009), but with adjustments and simplifications to suit our data and focus on the Swedish fund market and to examine the behaviour during the COVID-19 crisis. In this section, we describe our data set, explain the computation of Active Share and Tracking Error for each fund, outline our panel regressions of activeness and fund performance in general, and finally, analyse how activeness and performance change during the pandemic. The goal is to ensure a precise, robust, and feasible methodology that reliably addresses our research questions in the Swedish context.

A. Data Collection

To compute Active Share, we require fund-level holdings and weights. This data is retrieved from the Swedish Financial Supervisory Authority and includes the complete set of Swedish mutual funds with quarterly reports from 2018Q4 to 2024Q4. For each quarter, we retrieve the necessary variables: AUM, yearly management fee, fund ISIN, and the complete list of equity holdings (ISIN, name and portfolio weight). We then manually filter the sample from 2024Q4 and exclude any fund that holds non-European equity, fixed income assets, or is described as an index fund. We retain only funds present in all 25 quarters after applying the above filters, resulting in a sample of 85 funds (including one fund launched in 2019Q1). Daily fund NAV returns (net of fees) are obtained from Morningstar via the Swedish House of Finance database, using ISIN queries from the fund sample. The majority of funds use SEK as their base currency, with a few exceptions. We standardise all returns by converting non-SEK returns using daily FX rates from Riksbanken to ensure comparability. Historical index data is obtained from Nasdaq Global's central database[2]. We select 11 indices (Table I), each with different holding compositions, to match the structure of our fund sample. For each index, we retrieve quarterly stock names, ISINs and weights, along with daily returns. Non-SEK index returns are likewise converted using daily FX data. The Carhart factors are obtained from Kenneth French's data library. Specifically, we use the daily European Fama-French three-factor model (MRP, SMB, HML), along with the daily European momentum factor, which we combine into the standard Carhart four-factor model. For market

[2]Historical Index data were not available through the databases accessed from the school. We obtained access to Nasdaq Global's holdings database via direct request.

uncertainty, we use the VSTOXX index from ISS STOXX as a volatility proxy for the European market rather than the US-focused VIX index. Although our data set is constructed from several independent sources, we consider it reliable and well-suited for our study. The Swedish Financial Supervisory Authority, as the official regulatory filing agency for Swedish mutual funds, ensures comprehensive and standardised reporting on fund holdings. NAV returns from Morningstar via the Swedish House of Finance are widely used in academic and industry research. All currency conversions are handled consistently using daily FX rates from Riksbanken. While the index data is not obtained from standard academic databases, our access to Nasdaq Global's proprietary holdings database, a leading global index provider, likely provides an enhanced substitute. Furthermore, the Carhart four-factor model from Kenneth French's library and the VSTOXX measure are both widely accepted in asset pricing and volatility research. However, we acknowledge several limitations. Firstly, despite our extensive and well-defined manual filtering process, the risk of human error remains. Secondly, our requirement for complete data coverage may introduce survivorship bias. Lastly, the relatively small sample size and time horizon may limit the generalisability of our findings.

Table I
Overview of Selected Benchmark Indices

This table summarizes the 11 indices used to assign benchmark matches to Swedish mutual funds in the sample. The indices capture various segments of the Nordic and European equity markets, including small-, mid-, and large-cap exposures, sector-specific and country-specific benchmarks, and broad European indices.

Index	Description
OMXS30GI	30 largest and most traded stocks on Nasdaq Stockholm.
NOMXSCSEGI	Swedish small-cap companies on Nasdaq Stockholm.
OMXSPI	All listed stocks on Nasdaq Stockholm (broad market).
OMXSMCPI	Swedish mid-cap companies on Nasdaq Stockholm.
NOMXN120GI	120 most traded Nordic stocks across Nasdaq Stockholm, Copenhagen, Helsinki, and Oslo.
NQNO	Broad index of Norwegian stocks.
NQDK	Broad index of Danish stocks.
NQFI	Broad index of Finnish stocks.
NQDMEU	Developed European market stocks.
NOMXNCRGI	Nordic construction and real estate companies.
NQDMEUSCT	Developed Europe small-cap companies.

B. Computing Active Share and Tracking Error

Active Share: For each fund and quarter, we calculate Active Share relative to every available benchmark index using the following formula:

$$\text{Active Share}_{f,j,q} = \frac{1}{2}\sum_{i=1}^{N} |w_{f,i,q} - w_{j,i,q}|$$

where $w_{f,i,q}$ and $w_{j,i,q}$ denote the portfolio weights of stock i in fund f and index j during quarter q, respectively. We then compute the average Active Share over the 25 quarters and assign each fund to the benchmark index that yields the lowest average Active Share. All subsequent analyses related to Active Share are thus based on the assigned benchmark for each fund.

Tracking Error: For each fund and quarter, we also calculate the Tracking Error, presented in annualised terms. The calculation is based on daily return differences between the fund and its assigned benchmark:

$$\text{Tracking Error}_{\text{Yearly}} = \text{Stdev}(r_f - r_j) \times \sqrt{252}$$

where r_f and r_j represent the fund and benchmark index daily returns, respectively, and $\sqrt{252}$ reflects the typical number of trading days in a year.

Finally, we construct a panel dataset covering every fund and quarter, including Active Share, Tracking Error, AUM and Fee variables. In some instances, the Fee variable is missing from the Swedish Financial Supervisory Authority's dataset. Since the Fee is annual, we address this by applying a forward fill for the small number of missing observations. Table II shows summary statistics of our key variables.

Table II
Summary Statistics for Key Fund Characteristics

This table reports descriptive statistics for the variables used in the regression analysis. All values are based on the pooled sample of observations across all quarters. Percentages are shown for Active Share, Tracking Error, and Management Fee. AUM is reported in million SEK.

Variable	**N**	**Mean**	**Std**	**Min**	**25%**	**Median**	**75%**
Active Share (%)	2,124	64.32	16.86	12.96	52.56	65.00	76.28
Tracking Error (%)	2,124	10.52	4.77	0.74	7.22	9.47	12.83
Management Fee (%)	2,119	1.25	0.41	0.10	1.00	1.40	1.52
AUM (MSEK)	2,124	8,438.36	10,603.65	24.70	1,262.47	3,629.44	12,177.72

C. Active Share regression (General)

In line with Cremers and Petajisto (2009), we begin by examining the determinants of Active Share. Specifically, we estimate a series of panel regressions using quarterly fund-level data, incrementally introducing control variables to assess how they affect the model's explanatory power. The specifications are as follows:

$$\begin{aligned}
&(1) \quad \text{Active Share}_{i,q} = \beta_0 + \beta_1 \cdot \text{Tracking Error}_{i,q} + \varepsilon_{i,q} \\
&(2) \quad \text{Active Share}_{i,q} = \beta_0 + \beta_1 \cdot \text{Tracking Error}_{i,q} + \varepsilon_{i,q} \\
&(3) \quad \text{Active Share}_{i,q} = \beta_0 + \beta_1 \cdot \text{Tracking Error}_{i,q} + \beta_2 \cdot \ln(\text{AUM}_{i,q}) + \varepsilon_{i,q} \\
&(4) \quad \text{Active Share}_{i,q} = \beta_0 + \beta_1 \cdot \text{Tracking Error}_{i,q} + \beta_2 \cdot \text{Fee}_{i,q} + \varepsilon_{i,q} \\
&(5) \quad \text{Active Share}_{i,q} = \beta_0 + \beta_1 \cdot \text{Tracking Error}_{i,q} + \beta_2 \cdot \ln(\text{AUM}_{i,q}) \\
&\qquad\qquad + \beta_3 \cdot \text{Fee}_{i,q} + \varepsilon_{i,q}
\end{aligned}$$

Note: Specifications (2)–(5) include year fixed effects, which are omitted from Equations for clarity.

We apply the natural logarithm transformation to AUM for three reasons. First, it reduces skewness and heteroskedasticity due to the large variation in fund sizes within our sample. Second, it helps linearise multiplicative relationships and is consistent with how size effects are typically modelled in the mutual fund literature. Third, it simplifies the interpretation of coefficients, allowing changes in AUM to be interpreted in percentage terms rather than absolute amounts.

D. Fund Performance Regressions (General)

To investigate whether more active funds yield higher excess returns (returns over their assigned benchmark), we construct a 3x2 matrix based on Active Share and Tracking Error. The rows of the matrix represent three absolute levels of Active Share, while the columns represent two relative levels of Tracking Error. Unlike Cremers and Petajisto (2009), who group funds into quintiles, we use absolute thresholds for interpretability.

Specifically, we define three Active Share buckets: Closet Indexer ($< 60\%$), Moderately Active (60–80%), and Purely Active ($> 80\%$). This classification draws from Cremers and Petajisto's (2009) definition of closet indexers as funds with Active Share between 20% and 60%, and we extend their framework with evenly spaced thresholds. For Tracking Error, we classify funds as High or Low relative to the cross-sectional median.

Within each cell of the matrix, we pool daily net excess return (relative to the assigned benchmark) and estimate performance using the following regression:

$$\text{(6)} \qquad \text{Excess Return}_{i,t} = \alpha + \varepsilon_{i,t}$$

We also report heteroskedasticity-consistent t-values for the intercepts.

Next, following Cremers and Petajisto, we estimate risk-adjusted performance using the Carhart four-factor model, adjusted to reflect each fund's assigned benchmark. This ensures we evaluate performance relative to the index the fund should follow. We use this benchmark-adjusted version of the model for two main reasons. Firstly, mutual funds are required to track a specific benchmark, and both fund managers and investors evaluate performance against it. Secondly, investors typically care about whether a fund outperforms its benchmark, not just whether it earns a high alpha relative to general risk factors. The regression estimated in each cell of the matrix is:

$$\text{(7)} \qquad \text{Excess Return}_{i,t} = \alpha + \beta_1 \cdot \text{SMB}_t + \beta_2 \cdot \text{HML}_t + \beta_3 \cdot \text{MOM}_t + \varepsilon_{i,t}$$

Finally, to evaluate how Active Share and Tracking Error relate to excess return more broadly, we estimate a pooled OLS regression with the following specification:

$$
\begin{aligned}
(8) \qquad \text{Excess Return}_{i,t} = {} & \beta_0 + \beta_1 \cdot \text{Active Share}_{i,q} + \beta_2 \cdot \text{Tracking Error}_{i,q} \\
& + \beta_3 \cdot \ln(\text{AUM}_{i,q}) + \beta_4 \cdot \text{Fee}_{i,q} + \beta_5 \cdot \text{SMB}_t \\
& + \beta_6 \cdot \text{HML}_t + \beta_7 \cdot \text{MOM}_t + \varepsilon_{i,t}
\end{aligned}
$$

Since all performance regressions use excess return relative to each fund's assigned benchmark as the dependent variable, we do not include year fixed effects in any specification, as construction already accounts for market-wide variation.

In this setup, i denotes the funds, t represents trading days, and q denotes the quarter. Since our excess return data is daily while our fund characteristics are quarterly, we make the following adjustments. Firstly, we assign each daily observation to its respective quarter. Secondly, we forward-fill each fund's latest available quarterly characteristic across all daily returns within that quarter, assuming these variables remain constant over the quarter. The resulting coefficients capture the average marginal effect of each variable on daily excess return.

E. COVID-19 Event Analysis – Changes in Active Share

To begin our COVID-19 analysis, we plot the evolution of average Active Share over time, both for the whole fund sample and separately by buckets. For visual clarity and to avoid complications of funds switching categories during the period, we fix the bucket classification based on each fund's average Active Share over the entire period. This ensures a stable grouping that allows us to track how different types of funds responded during the crisis. To complement the descriptive figure, we also report a summary table showing the average Active Share from 2019Q4 to 2020Q2 for the full sample and each fixed bucket.

F. COVID-19 Event Analysis – Performance Analysis

This step examines whether higher Active Share improved performance during the COVID-19 crisis. To test this, we introduce a dummy variable identifying the crisis period and interact it with Active Share. Following Fidelity International's (n.d.) definition, we define periods of heightened market stress as those in which the VIX index exceeds 30. Using this threshold and its European equivalent, the VSTOXX index, we define the COVID-19 crisis window as the period between February 27, 2020, and May 7, 2020, during which the VSTOXX consistently remained above 30.

We pool all funds and estimate the following regression:

$$
\begin{aligned}
(9) \qquad \text{Excess Return}_{i,t} = {} & \beta_0 + \beta_1 \cdot \text{Active Share}_{i,q} + \beta_2 \cdot \text{COVID}_t \\
& + \beta_3 \cdot (\text{Active Share}_{i,q} \times \text{COVID}_t) \\
& + \beta_4 \cdot \text{Tracking Error}_{i,q} + \beta_5 \cdot \ln(\text{AUM}_{i,q}) + \beta_6 \cdot \text{Fee}_{i,q} \\
& + \beta_7 \cdot \text{SMB}_t + \beta_8 \cdot \text{HML}_t + \beta_9 \cdot \text{MOM}_t + \varepsilon_{i,t}
\end{aligned}
$$

The coefficient on the COVID dummy (β_2) captures the average impact of the crisis period on excess return across all funds. The key coefficient of interest is the interaction term (β_3), which reflects the additional return associated with higher Active Share (0% to 100%) during the COVID-19 period.

In line with previous regressions, we also analyse performance separately by fund bucket (Closet, Moderate, Pure). For each bucket, we estimate the following specification:

$$\text{(10)} \quad \text{Excess Return}_{i,t} = \alpha + \beta_1 \cdot \text{COVID}_t + \beta_2 \cdot \text{SMB}_t + \beta_3 \cdot \text{HML}_t + \beta_4 \cdot \text{MOM}_t + \varepsilon_{i,t}$$

In this specification, the COVID coefficient (β_1) captures the change in average excess return during the COVID period relative to non-COVID periods. The intercept (α) reflects the average excess return outside the crisis window.

G. General Uncertainty Performance Analysis

Lastly, we examine whether the relationship between Active Share and performance generalises to other periods of heightened uncertainty. To do so, we follow a similar approach to the COVID-19 analysis but replace the COVID dummy with a broader indicator based on the VSTOXX index. Specifically, we define a binary variable equal to 1 when the VSTOXX exceeds 30, signalling high market uncertainty, and zero otherwise.

We begin with a pooled regression, consistent with our earlier COVID specification:

$$\begin{aligned} \text{(11)} \quad \text{Excess Return}_{i,t} = {} & \beta_0 + \beta_1 \cdot \text{Active Share}_{i,q} + \beta_2 \cdot \text{VSTOXX Dummy}_t \\ & + \beta_3 \cdot (\text{Active Share}_{i,q} \times \text{VSTOXX Dummy}_t) \\ & + \beta_4 \cdot \text{Tracking Error}_{i,q} + \beta_5 \cdot \ln(\text{AUM}_{i,q}) + \beta_6 \cdot \text{Fee}_{i,q} \\ & + \beta_7 \cdot \text{SMB}_t + \beta_8 \cdot \text{HML}_t + \beta_9 \cdot \text{MOM}_t + \varepsilon_{i,t} \end{aligned}$$

The VSTOXX coefficient (β_2) captures the average change in excess return during periods of elevated market uncertainty, while the interaction term (β_3) reflects the additional return associated with higher Active Share (0% to 100%) in those periods.

We then estimate the relationship separately for each Active Share bucket. The specification in this case is:

$$\text{(12)} \quad \text{Excess Return}_{i,t} = \alpha + \beta_1 \cdot \text{VSTOXX Dummy}_t + \beta_2 \cdot \text{SMB}_t + \beta_3 \cdot \text{HML}_t + \beta_4 \cdot \text{MOM}_t + \varepsilon_{i,t}$$

In this setup, the intercept (α) represents average excess return during normal market conditions (VSTOXX < 30), while the VSTOXX coefficient (β_1) captures the shift in return during periods of market uncertainty.

All regressions are estimated in Python, with Newey-West standard errors applied to address heteroscedasticity and serial correlation. We include fund-level controls such as Tracking Error, ln(AUM), and Fee for pooled regressions to mitigate omitted variable bias. In contrast, we omit these controls in the bucketed regressions, as the groupings are designed to reflect differences in activeness and reduce potential noise. We also conduct variance inflation factor (VIF) tests to assess potential multicollinearity. All calculations are implemented using standard packages, ensuring reproducibility and computational efficiency.

IV. Empirical Results and Discussion

A. Determinants of Active Share

To understand what drives Active Share, we estimate a series of OLS regressions with control variables, as seen in Table III. This aligns with Cremers and Petajisto (2009), but uses slightly different control variables.

Across all specifications, Tracking Error is the strongest and most statistically significant predictor of Active Share. The coefficient remains positive and highly significant throughout, ranging from 1.15 ($t = 10.76$) in the first model to 1.20 ($t = 10.78$) in the full model. This finding supports the idea that funds which deviate more from their benchmark returns also do so in holding, which is consistent with the idea that Active Share is a measure of true activeness.

Fee is also positively associated with Active Share. In the full model, the coefficient is 13.53 ($t = 12.03$), indicating that more expensive funds tend to be more active. This may reflect higher research costs or deliberate positioning away from passive investments. The result is consistent with the view that, at least in part, fees compensate for active management, and you get what you pay for.

Fund size, measured as the natural logarithm of assets under management (ln(AUM)), is negatively associated with Active Share (-1.64, $t = -6.42$), suggesting that larger funds are less active. This relationship likely reflects scalability and liquidity constraints. Becker and Vaughan (2001) argue that as funds grow, “portfolio managers lose flexibility: it becomes harder to switch in and out of positions.” While this statement is not empirically tested in their paper, it highlights a plausible constraint that could explain why larger funds tend to be less active. Cremers and Petajisto (2009) observe a similar pattern, where Active Share declines above $1 billion in AUM. While we do not establish our exact turning point, the significant negative coefficient suggests the same pattern.

The year fixed effects yield mixed results but reveal interesting patterns. The coefficients for 2020 and 2022 are negative across all specifications. These years correspond to the beginning of the COVID-19 pandemic and the Russian invasion of Ukraine, two periods of heightened uncertainty. While the significance of the coefficients varies, the negative signs suggest that many fund managers temporarily reduce activeness during these shocks.

The results highlight how key fund characteristics, particularly Tracking Error, AUM and Fee, help explain variation in Active Share in Swedish equity funds. These findings suggest that structural factors and managerial choices shape the degree of activeness. Building on this, the next step examines whether higher activeness improves performance.

Table III
Determinants of Active Share

This table presents OLS regressions of Active Share on fund characteristics and year fixed effects from 2019 to 2024 (base year = 2018). Each column represents a different model specification, incrementally including Ln AUM, Fee, and year dummies. z-statistics (Newey-West standard errors) are reported in parentheses. *Note:* *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: Active Share				
	(1)	(2)	(3)	(4)	(5)
Tracking Error	1.149***	1.498***	1.409***	1.276***	1.196***
	(10.76)	(12.26)	(11.59)	(11.45)	(10.78)
Ln AUM			-1.752***		-1.637***
			(-6.91)		(-6.42)
Fee				13.739***	13.532***
				(11.85)	(12.03)
2019 (dummy)		4.188**	4.326**	3.679**	3.816**
		(2.16)	(2.26)	(1.97)	(2.06)
2020 (dummy)		-4.602**	-3.899*	-3.789*	-3.144
		(-2.17)	(-1.87)	(-1.87)	(-1.57)
2021 (dummy)		3.028	4.043**	3.434*	4.376**
		(1.49)	(2.01)	(1.76)	(2.25)
2022 (dummy)		-5.259**	-4.177*	-3.967*	-2.975
		(-2.47)	(-1.99)	(-1.94)	(-1.46)
2023 (dummy)		-1.641	-0.797	-2.098	-1.303
		(-0.80)	(-0.39)	(-1.06)	(-0.66)
2024 (dummy)		1.294	2.176	0.356	1.194
		(0.64)	(1.10)	(0.18)	(0.61)
Constant	52.204***	49.009***	87.634***	34.115***	70.431***
	(43.80)	(23.10)	(14.57)	(14.73)	(11.28)
Observations	2,119	2,119	2,119	2,119	2,119
R-squared	0.106	0.140	0.166	0.249	0.272

B. Active Share and Excess Return Performance

In this section, we investigate whether funds with higher Active Share deliver higher returns over the full sample period. We begin by examining Active Share when divided into buckets, and then present a pooled regression treating Active Share as a continuous variable. In Table IV, we examine two measures of excess returns: raw benchmark-adjusted excess returns (Panel A) and risk-adjusted excess returns from a Carhart four-factor model (Panel B). Among the Closet and Moderate buckets, we find no evidence of either outperformance or underperformance. The Closet Indexers' coefficient signs vary depending on the volatility level and whether the excess returns are adjusted for Carhart factors. However, none are statistically significant. The most notable finding is that we find no support for the claim that high Active Share leads to significant positive excess return, as Cremers and Petajisto (2009) suggested. However, we find differences within the Pure bucket, where those with low Tracking Error have a significant average excess return of -4.55% (t = -2.67) after adjusting for Carhart factors. Meanwhile, the bucket as a whole has an excess return of -2.68% with lower significance (t = -1.60). However, the results in Panel A, presenting benchmark-adjusted returns, do not show a significant underperformance for the most active funds, indicating that the underperformance is likely driven by factor exposures rather than poor stock-picking. The results suggest that the funds with the highest Active Share underperform in Sweden, although the results should be interpreted with caution, as there is low significance.

Table IV
Fund Performance by Active Share and Tracking Error Groupings

This table reports annualized excess returns for Swedish equity mutual funds grouped by average Active Share (Closet: < 60%, Moderate: 60–80%, Pure: > 80%) and Tracking Error (Low/High). Panel A presents benchmark-adjusted returns. Panel B shows benchmark-adjusted Carhart alphas. All regressions are estimated separately for each group using Newey–West standard errors. Reported values are annualized net excess returns (in percent), with *t*-statistics in parentheses. The sample period is 2018–2024. *Note:* *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Active Share group	Low	High	All	High–Low
Panel A: Benchmark-adjusted returns with Newey–West standard errors				
Closet	0.24 (0.42)	-1.39 (-1.16)	-0.58 (-0.37)	-0.69 (-0.26)
Moderate	1.04 (1.54)	0.64 (0.57)	0.84 (1.06)	-0.44 (-0.19)
Pure	-3.51** (-2.02)	-0.69 (-0.39)	-2.10 (-1.21)	1.31 (0.36)
All	0.29 (0.69)	-0.37 (-0.49)	-0.04 (-0.09)	-0.77 (-0.35)
Panel B: Carhart benchmark-adjusted returns with Newey–West standard errors				
Closet	-0.13 (-0.24)	0.59 (0.55)	0.23 (0.16)	-0.57 (-0.23)
Moderate	-0.00 (-0.00)	1.00 (0.95)	0.50 (0.47)	-0.42 (-0.19)
Pure	-4.55*** (-2.67)	-0.82 (-0.52)	-2.68* (-1.60)	2.05 (0.60)
All	-0.41 (-1.00)	0.41 (0.60)	0.00 (0.00)	-0.36 (-0.18)

Next, we evaluate Active Share as a continuous variable in a pooled regression framework, where we control for Tracking Error, AUM, Fee and Carhart factors. This allows us to isolate the marginal effect of Active Share on fund performance. The results, presented in Table V, confirm our earlier findings. The coefficient on Active Share is close to zero and insignificant. Overall, our findings provide no evidence that Active Share, as a measure, reliably explains excess return for Swedish mutual funds. Neither the bucket analysis nor the pooled regression shows evidence of a consistent relationship between Active Share and excess return.

Table V
OLS Regression of Annualised Excess Return on Active Share and Fund Characteristics

This table reports an OLS regression of daily fund excess return on Active Share and control variables. Excess returns are annualised and expressed in percent. t-statistics are based on Newey–West standard errors. Factor loadings (SMB, HML, MOM) are not scaled and represent daily Carhart four-factor exposures. The sample includes 103,973 fund-day observations over the period 2018–2024. *Note:* *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Excess Return (%)	
	Coefficient	t-statistic
Intercept	2.52	0.60
Active Share	-0.16	-0.07
Tracking Error	0.18	0.15
Fee	-2.54	-0.29
Ln AUM	-1.17	-0.50
SMB	0.0038***	42.17
HML	-0.0001***	-2.90
MOM	0.0006***	16.00
Observations	103,973	
R-squared	0.066	

Our findings contrast with the results of Cremers and Petajisto (2009), who document a significant and positive relationship between Active Share and excess return. There are several possible explanations for our results. First, when a fund manager identifies an arbitrage opportunity expected to lead to excess return, institutional frictions may prevent them from executing the trade in a timely or scalable manner. Duffie (2010) highlights that capital frictions, including time to raise capital and search costs for trading counterparties, can cause capital to move slowly, limiting managers' ability to respond quickly to trading opportunities.

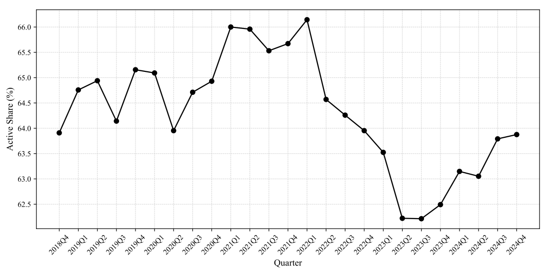
Second, one possible explanation lies in one of the most foundational theories in financial economics. Fama (1970) argues that security prices fully reflect all available information at any given time, implying that markets are efficient. If this holds, fund managers cannot generate alpha from stock-picking, even if they deviate substantially from their benchmark.

Third, the nature of the Swedish market may constrain the potential for excess return. Most Swedish mutual funds are regulated under the UCITS framework, which stipulates that no more than 10% of holdings can be allocated to a single security, and that the five largest holdings together cannot exceed 40% of the fund's assets (European Commission, 2016). These restrictions limit managers' ability to hold concentrated positions, meaning that even high-Active Share funds cannot allocate heavily to a few high-conviction stocks.

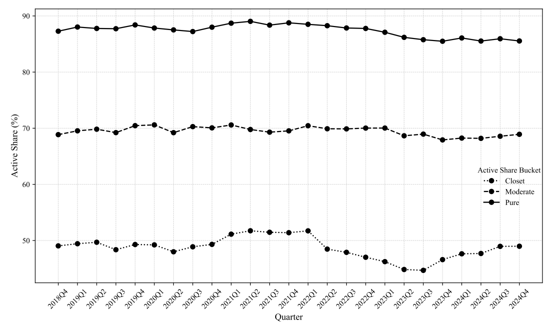
Lastly, there are several potential reasons why our results deviate from Cremers and Petajisto (2009) include, but are not limited to, a shorter sample period, a smaller number of funds and a slightly modified methodology. Additionally, a broader set of indices could improve the precision of benchmark assignments.

C. COVID-19 impact on Active Share

Before turning to crisis-period performance, we briefly examine how the onset of COVID-19 affects fund managers' Active Share levels. The year-fixed effects in our earlier Active Share regressions already hint at a notable decline in Active Share in 2020, and we investigate this effect more directly here. The COVID-19 pandemic began in the first quarter of 2020, triggering a swift and severe stock market downturn. This results in fund managers adjusting their activeness in response, as seen in Figure 2. This also reveals important dynamics in how mutual fund managers adjust their investment strategies during periods of heightened uncertainty. As shown in Panel A, average Active Share declined modestly during the initial stages of COVID-19 in early 2020, but rebounded by mid-2021. Another interesting finding is the more pronounced and persistent decline beginning in early 2022, coinciding with the invasion of Ukraine. This second drop in Active Share is steeper and more prolonged than the COVID-related decline, reaching its lowest point in 2023Q3, before recovering slightly thereafter. Regarding the different buckets, Pure funds remain highly consistent throughout both crises. Their Active Share stays close to 88% (Panel B), showing little to no reaction to the COVID-19 shock or the war in Ukraine. This suggests that truly active managers stick to their strategies even during market turbulence. Moderate funds also display relative stability, hovering just below 70% with only minimal dips. These funds appear to maintain their core investment strategies despite external shocks. In contrast, Closet Indexers display the greatest responsiveness to uncertainty; their Active Share declines during both crises, with the sharpest drop occurring during the Ukraine invasion.



Panel A: All Funds



Panel B: By Active Share Bucket

Figure 2. Evolution of Active Share from 2018Q4 to 2024Q4. This figure shows the evolution of average Active Share for Swedish equity mutual funds over time. Panel A displays the average across all funds in the sample. Panel B presents the same measure, separated by fixed Active Share buckets (Closet Indexers: <60%, Moderate: 60–80%, Pure: >80%). Buckets are assigned based on each fund's average Active Share during the sample period to ensure a stable classification.

These findings, although different in magnitude across fund types (Table VI), align with the career concerns hypothesis proposed by Chevalier and Ellison (1999). They argue that younger fund managers, in particular, face stronger incentives to avoid unsystematic risk and align their portfolios more closely to benchmarks, to reduce the risk of termination. Their evidence suggests managers are more likely to be terminated when their holdings deviate from conventional sector allocations or risk levels, especially during uncertain periods. Whether this behaviour benefits investors or instead reflects agency problems is a question we address in the subsequent performance analysis.

Table VI
Quarterly Mean Active Share by Fund Group Before and During COVID-19

This table reports the average Active Share for Swedish equity mutual funds, grouped by Active Share level. Funds are classified as Closet (Active Share $< 60\%$), Moderate (60–80%), and Pure (Active Share $> 80\%$). We present mean Active Share across quarters from 2019Q4 to 2020Q2. The final column reports the average number of funds (N) in each group.

Group	**2019Q4**	**2020Q1**	**2020Q2**	**Change**	**N**
Closet	49.29	49.23	47.99	-1.30	34
Moderate	70.46	70.60	69.21	-1.25	36
Pure	88.40	87.85	87.51	-0.89	15
All	65.16	65.09	63.95	-1.21	85

D. Fund Performance During the COVID-19 Crisis

Next, we use two complementary approaches to examine performance during the outbreak of COVID-19, a period of heightened uncertainty. First, we estimate a pooled regression with the full sample of funds to examine the relationship between Active Share and excess return, including an interaction term from Active Share and the COVID-19 period. Second, we estimate separate regressions for each of the Active Share buckets to analyse how funds with different levels of activeness perform. The COVID-19 window is defined as 2020/02/27 - 2020/05/07. Table VII shows our results from the pooled regression, which controls for fund characteristics including Tracking Error, Fee, AUM and other common risk factors using Carhart factors. The interaction term between Active Share and COVID is positive and highly significant (0.34%, $t = 3.21$), suggesting that higher activeness improves excess return during the crisis. Each additional ten percentage points of Active Share corresponds to a 3.4 basis point increase in daily excess return. Moreover, the coefficient on the COVID dummy is negative and statistically significant (-0.18%, $t = -2.80$), indicating that funds, on average, perform worse during COVID-19 compared to the rest of the sample period. Since both the dummy and interaction coefficients are significant, we can also state that the threshold for delivering superior returns compared to the baseline period is roughly an Active Share of 50%.

Table VII
OLS Regression of Daily Excess Return on Active Share, COVID-19 Dummy, and Interaction

This table reports an OLS regression of daily fund excess return on Active Share, a COVID-19 dummy, and their interaction. The regression includes controls for fund characteristics and daily Carhart four-factor exposures. Excess returns are expressed in percent per day. We do not annualise coefficients here because the COVID-19 dummy captures an isolated, short-lived crisis. t-statistics are based on Newey–West standard errors. The sample includes 103,973 fund-day observations over the period 2018–2024. *Note:* *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Excess Return (%)	
	Coefficient	t-statistic
Intercept	0.020	0.70
Active Share	-0.0075	-0.80
COVID dummy	-0.18***	-2.80
Active Share × COVID	0.34***	3.21
Tracking Error	-0.0003	-0.60
Fee	-0.0014	-0.42
Ln AUM	-0.0002	-0.27
SMB	0.38***	42.15
HML	-0.01***	-2.71
MOM	0.06***	16.08
Observations	103,973	
R-squared	0.066	

Our results from the separate regression, presented in Table VIII, reveal differences across the Active Share categories. The most Active funds have a negative intercept coefficient (-0.0097%, t = -2.11) and a positive COVID-19 coefficient (0.14%, t = 2.74). The positive COVID dummy indicates that these funds improve their excess return significantly during COVID-19. Taken together, the most active funds earn an average daily excess return of 0.13% (-0.0097% + 0.14%) during the COVID-19 window.

Moderately Active funds also experience an improvement in performance (0.04%), although the result is less statistically significant (t = 1.67) and the effect size is smaller compared to Pure funds. The results also indicate that funds in the Moderate category, on average, achieve a daily excess return of 0.044% during the COVID-19 window. However, these results should be interpreted with caution due to the lower significance of both the intercept and the COVID dummy. Lastly, Closet Indexers show no significant results for either the intercept or the COVID dummy. We find no evidence that their performance improves or deteriorates during the COVID-19 period.

Table VIII
OLS Regressions of Daily Excess Return by Active Share Group with COVID-19 Dummy

This table reports OLS regressions of daily excess return for Swedish equity mutual funds, estimated separately for each Active Share group: Closet (Active Share < 60%), Moderate (60–80%), and Pure (> 80%). The regressions are run on the full sample period (2018–2024), and the COVID-19 crisis period (Feb 27–May 7, 2020) is captured using a dummy variable. Regressors include the COVID-19 dummy and Carhart four-factor exposures. Excess returns are expressed in percent per day. t-statistics based on heteroskedasticity- and autocorrelation-consistent (HAC) standard errors are reported in parentheses. *Note:* *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Closet	Moderate	Pure
Intercept	0.0016 (0.87)	0.0040* (1.84)	-0.0097** (-2.11)
COVID dummy	-0.0100 (-0.58)	0.0400* (1.67)	0.1400*** (2.74)
SMB	0.4300*** (31.00)	0.3300*** (24.06)	0.3900*** (16.92)
HML	-0.0010 (-0.20)	0.0090 (1.32)	-0.1000*** (-6.55)
MOM	0.0400*** (8.00)	0.0600*** (10.77)	0.1200*** (9.27)
Observations	43,947	43,468	16,808
R-squared	0.092	0.049	0.077

Our findings show the importance of Active Share during the most uncertain period of the COVID-19 outbreak, with support from both the pooled regression and the bucket-level analysis. These findings contrast with Pastor and Vorsatz (2020), who report that 74% of U.S. active equity funds underperform during COVID-19. Although they do not examine Active Share directly, a similar pattern of underperformance might be expected in Sweden. Instead, the most active funds significantly outperform during the COVID-19 period. That said, our findings capture only the uncertainty related to COVID-19. It is possible that specific market conditions during this window create an environment particularly favourable to highly active managers. To further understand the role of Active Share under uncertainty, we extend the analysis in the next section to examine market-wide uncertainty across the full sample period, where a more nuanced discussion is presented.

E. Fund Performance during general market uncertainty

Using a similar structure to the previous section on COVID-19 performance, we now extend our analysis to examine broader periods of uncertainty. This extension incorporates additional episodes of market turbulence, such as Russia's invasion of Ukraine. In the regressions, the VSTOXX index serves as a proxy for market uncertainty, and we define a High VSTOXX dummy as a daily VSTOXX value exceeding 30.

Our findings indicate a similar pattern to that observed during COVID-19. The pooled regression, presented in Table IX, shows that the interaction term between Active Share and VSTOXX is highly significant (t = 5.02) with a coefficient of 0.27%. Each additional ten percentage points of Active Share corresponds to a 2.7 basis point improvement in daily excess return during periods of high uncertainty, slightly lower than the corresponding estimate for the COVID-19 period.

Table IX
OLS Regression of Daily Excess Return on Active Share, High-VSTOXX Dummy, and Interaction Term

This table reports an OLS regression of daily fund excess returns on Active Share, a dummy variable equal to one when the VSTOXX index exceeds 30 (high volatility), and their interaction. Fund characteristics and Carhart four-factor exposures are included as controls. Coefficients are expressed in percent. t-statistics based on Newey–West standard errors are shown in parentheses. *Note:* *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Excess Return (%)	
	Coefficient	t-statistic
Intercept	0.030	1.24
Active Share	-0.020**	-2.41
High VSTOXX dummy	-0.150***	-4.73
Active Share × VSTOXX	0.270***	5.02
Tracking Error	-0.0003	-0.58
Fee	-0.0015	-0.42
Ln AUM	-0.0003	-0.36
SMB	0.0038***	42.21
HML	-0.0001***	-2.81
MOM	0.0006***	16.01
Observations	103,963	
R-squared	0.066	

The separate regressions, based on Active Share buckets, are presented in Table X. The most active funds achieve a statistically significant increase of 0.09% in daily excess return during periods of high uncertainty (t = 3.47), while the intercept is also significant but negative (-0.01%, t = -3.01). Combined, these funds generate an average daily excess return of 0.08% (-0.01% + 0.09%) under high uncertainty. In contrast to the COVID-19 specific regression, Moderately Active funds do not exhibit any statistically significant coefficients for either the VSTOXX dummy or the intercept. Notably, Closet Indexers experience a significant decline in relative excess return (-0.02%, t = -1.99) during high volatility periods. However, the intercept is positive (0.003%, t = 1.78), corresponding to a daily excess return of -0.02%. No such significance is observed in the COVID-19 results.

Table X
OLS Regression of Daily Excess Return on VSTOXX Dummy and Carhart Factors by Active Share Group

This table shows regression results of daily fund excess returns on a dummy for high market volatility (defined as VSTOXX >30) and Carhart four-factor exposures. Results are estimated separately for each Active Share group (Closet: <60%, Moderate: 60–80%, Pure: >80%). All coefficients are in percent. z-statistics based on heteroskedasticity- and autocorrelation-consistent (HAC) standard errors are reported in parentheses. *Note:* *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Closet	Moderate	Pure
Intercept	0.0033* (1.78)	0.0033 (1.49)	-0.0100*** (-3.01)
High VSTOXX dummy	-0.0200** (-1.99)	0.0200 (1.56)	0.0900*** (3.47)
SMB	0.0043*** (31.03)	0.0033*** (24.06)	0.0039*** (16.92)
HML	-0.0020 (-0.26)	0.0090 (1.24)	-0.1000*** (-6.58)
MOM	0.0400*** (8.02)	0.0600*** (10.72)	0.1200*** (9.16)
Observations	43,947	43,468	16,808
R-squared	0.092	0.049	0.077

These results highlight the importance of Active Share during uncertain market conditions. The most active funds consistently outperform, while Closet Indexers tend to underperform. Our results suggest that active fund managers are able to exploit market mispricing during periods of turbulence. This stands in contrast to earlier research emphasising the impossibility of earning persistent excess returns in efficient markets (Fama, 1970), suggesting that market efficiency may break down under extreme uncertainty. Furthermore, the results also challenge the notion that institutional frictions prevent active managers from executing high-conviction trades (Duffie, 2010), as our result indicates that such constraints do not lead to underperformance in practice.

As discussed in Section C, the average level of Active Share declines during the COVID-19 crisis and after Russia's invasion of Ukraine in 2022. However, our results show that these are precisely the periods when a high Active Share adds the most value for investors. This behaviour may partly be explained by Chevalier and Ellison (1999), who find that fund managers, particularly younger ones, tend to reduce risk exposure due to career concerns and fear of job termination. It is reasonable to assume that such concerns intensify during turbulent markets, leading managers to shift portfolios closer to their benchmarks.

This behaviour is consistent with a principal-agent problem presented by Jensen and Meckling (1976), in which the agent acts in their own interest rather than in the interest of the principal. In this context, the principal (the investor) pays a fee for active stock selection, while the agent (the fund manager) acts conservatively by reducing Active Share to limit short-term deviations from the benchmark, thus lowering the risk of termination. While our results support this interpretation, additional empirical research is needed before drawing definitive conclusions.

Given the significance of these findings and their potential implications, we next turn to a set of robustness checks to assess the reliability of our results.

V. Robustness Checks

To validate the reliability of our findings, we implement two primary robustness tests. First, we examine whether the results depend on how the Active Share buckets are defined. In our main analysis, funds are grouped into Closet (<60%), Moderate (60-80%) and Pure (>80%). As a robustness check, we redefine these thresholds using a more conservative classification: <50%, 50-70%, and >70%. Table XI shows that the main pattern persists. Pure funds continue to deliver higher excess returns during COVID-19. The coefficients remain consistent, and while the significance levels are slightly lower, they still support our main conclusions.

Table XI

Robustness Test of Fund Performance During COVID-19 by Active Share Group Using Alternative Buckets

This table reports OLS regression results of daily fund Excess Return on a COVID-19 dummy and Carhart four-factor model (SMB, HML, MOM), estimated separately for three Active Share groups: Closet (<50%), Moderate (50–70%), and Pure (>70%). All coefficients are in percent. Excess Return is measured relative to each fund's assigned benchmark. The COVID-19 period is defined as February 27 to May 7, 2020. z-statistics based on HAC standard errors (5 lags) are reported in parentheses. *Note:* *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Closet (<50%)	**Moderate (50–70%)**	**Pure (>70%)**
Intercept	0.0026 (1.18)	0.0003 (0.12)	0.0004 (0.15)
COVID dummy	-0.002 (-0.08)	0.007 (0.30)	0.09*** (2.85)
SMB	0.41*** (23.01)	0.38*** (27.79)	0.36*** (22.68)
HML	0.01* (1.76)	-0.003 (-0.48)	-0.04*** (-4.56)
MOM	0.04*** (6.89)	0.04*** (7.39)	0.10*** (13.11)
Observations	24,705	42,297	37,221
R-squared	0.082	0.070	0.062

Second, we test whether our results are sensitive to the choice of threshold for defining high market uncertainty. In the baseline specification, we use VSTOXX > 30 as the cutoff. As a robustness test, we re-estimate the regression using a more conservative threshold of VSTOXX > 20. Table XII shows that the results remain similar: the performance gap between high and low Active Share funds during volatile periods is still strong, further reinforcing the robustness of our conclusions.

Table XII
Robustness Test of Fund Performance During High VSTOXX Periods by Active Share Group Using Original Buckets

This table reports OLS regression results of daily fund Excess Return on a high-VSTOXX dummy and the Carhart four-factor model (SMB, HML, MOM), estimated separately for Closet (<60%), Moderate (60–80%), and Pure (>80%) Active Share groups. All coefficients are in percent. The high-VSTOXX dummy equals 1 when the VSTOXX index exceeds 20, and 0 otherwise. Excess Return is measured relative to each fund's assigned benchmark. Coefficients are shown with z-statistics (HAC standard errors, 5 lags) in parentheses. *Note:* *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Closet (<60%)	**Moderate (60–80%)**	**Pure (>80%)**
Intercept	0.0029 (1.35)	-0.0037 (-1.40)	-0.0176*** (-4.50)
High VSTOXX	-0.004 (-0.98)	0.02*** (4.25)	0.05*** (4.29)
SMB	0.43*** (30.94)	0.33*** (24.04)	0.39*** (16.88)
HML	-0.001 (-0.13)	0.008 (1.10)	-0.11*** (-6.73)
MOM	0.04*** (8.00)	0.06*** (10.76)	0.12*** (9.20)
Observations	43,947	43,468	16,808
R-squared	0.092	0.049	0.077

In addition to these two main tests, we evaluate the potential presence of multicollinearity to ensure that our regression assumptions hold. To do so, we conduct Variance Inflation Factor (VIF) tests. Table XIII presents the results for the pooled regression specifications, while Table XIV shows the results for the bucketed analysis. In all models, the VIF values for explanatory variables remain well below the commonly accepted threshold of 5, indicating that multicollinearity is not a concern. This provides additional reassurance regarding the credibility and robustness of our findings.

Table XIII
Variance Inflation Factors (VIFs) from the Pooled Regression Model

This table reports VIF values from the pooled OLS regression including Active Share, fund characteristics, and Carhart four-factor exposures. VIFs indicate the degree of multicollinearity among regressors. Values near or above 10 are typically considered problematic.

Variable	VIF
Intercept (const)	232.29
Active Share	1.36
Tracking Error	1.11
Fee	1.23
Ln AUM	1.02
SMB	1.04
HML	1.14
MOM	1.11

Table XIV
Variance Inflation Factors (VIFs) from Carhart Regressions with COVID and VSTOXX Dummies

This table reports VIF values from two Carhart four-factor regressions that include either a COVID-period dummy or a high-VSTOXX dummy (indicating periods of market uncertainty). All values are well below conventional multicollinearity thresholds (typically VIF > 10).

Variable	COVID Dummy + Carhart	High VSTOXX + Carhart
Constant	1.033	1.100
COVID dummy / High VSTOXX dummy	1.012	1.006
SMB	1.036	1.036
HML	1.152	1.144
MOM	1.108	1.108

VI. Conclusion

This study examines the role of Active Share in Swedish equity mutual funds across varying levels of market uncertainty, with particular focus on COVID-19 and broader periods of high uncertainty. We evaluate whether fund activeness, as measured by Active Share, is associated with differences in benchmark-adjusted excess returns and whether this relationship varies depending on the level of market uncertainty.

Over the full sample period, we find no evidence of a relationship between Active Share and excess return, whether treated as a continuous variable or through bucket classifications. These results suggest that Active Share is not a reliable predictor of fund outperformance in the Swedish market. This contrasts earlier findings based on U.S. mutual fund data, which suggest a positive relationship between Active Share and excess return (Cremers and Petajisto, 2009).

In contrast, Active Share gains predictive power during periods of heightened market uncertainty. During the COVID-19 window, funds with an Active Share above 80% earned an average daily excess return of 0.13%. Similar results emerge when extending the sample to periods when the VSTOXX index exceeds 30: highly active funds achieve a daily excess return of 0.09%, while Closet Indexers (Active Share <60%) underperform with an average daily excess return of -0.02%.

Our findings contribute to the Active Share debate by showing that high Active Share is associated with significantly higher excess returns during periods of market uncertainty. In contrast, no such relationship exists under normal market conditions. These results suggest Swedish investors should treat Active Share as a meaningful indicator only during volatile periods. Fund managers may also benefit from increasing Active Share during such times, as deviating from benchmark weights appears to be rewarded in uncertain environments.

Future research could extend this analysis through cross-country comparisons, investigating how Active Share relates to performance during crises across different regulatory and market structures. Such studies would clarify the role of country-specific factors, such as regulation, retail investor engagement, and financial development, in shaping the relevance of Active Share in turbulent environments. Given Sweden's distinctive features, including high retail participation and UCITS-based regulation, it remains an open question whether these findings generalise to other markets.

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Appendix

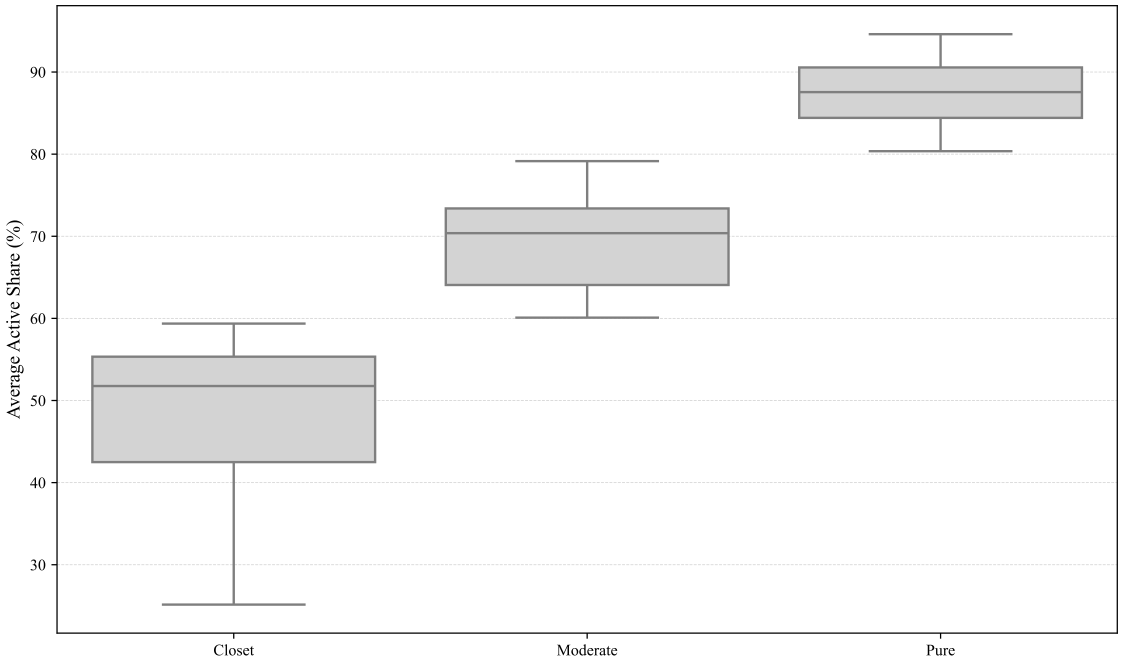

Figure A.1

Average Active Share by Fund Group.
This figure shows the distribution of average Active Share by fund group, divided into Closet (Active Share < 60%), Moderate (60–80%), and Pure (> 80%) categories. It visually supports the classification scheme used throughout the analysis.

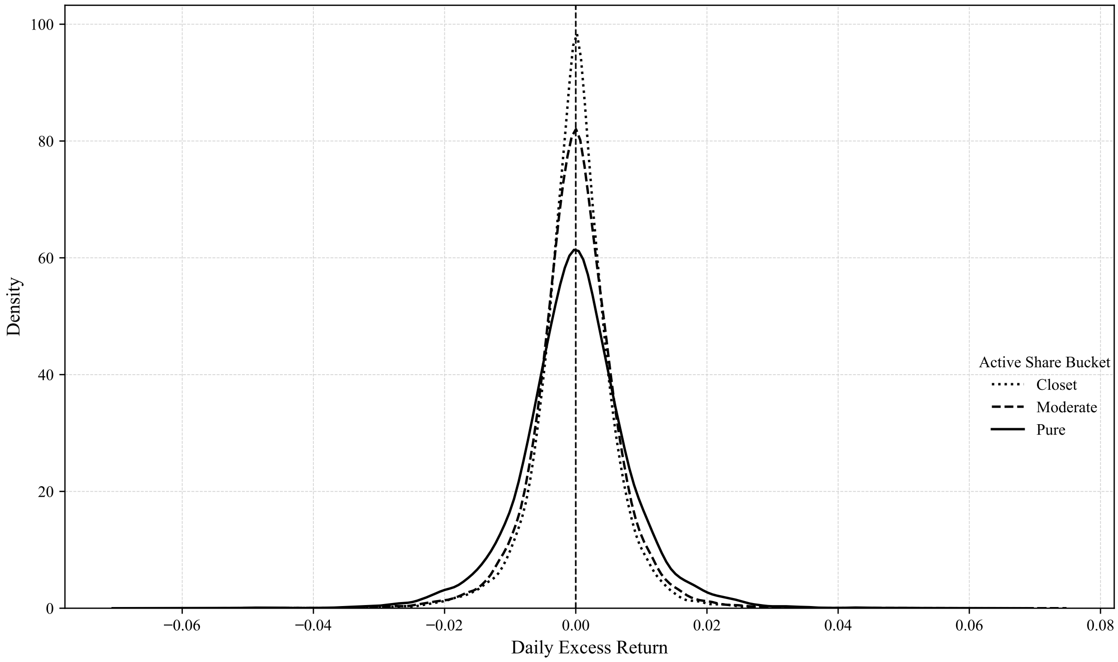

Figure A.2

Distribution of Daily Excess Returns by Fund Group.
This figure displays the kernel density estimates of daily excess return distributions by Active Share group. It illustrates how return profiles differ across Closet, Moderate, and Pure funds over the sample period.

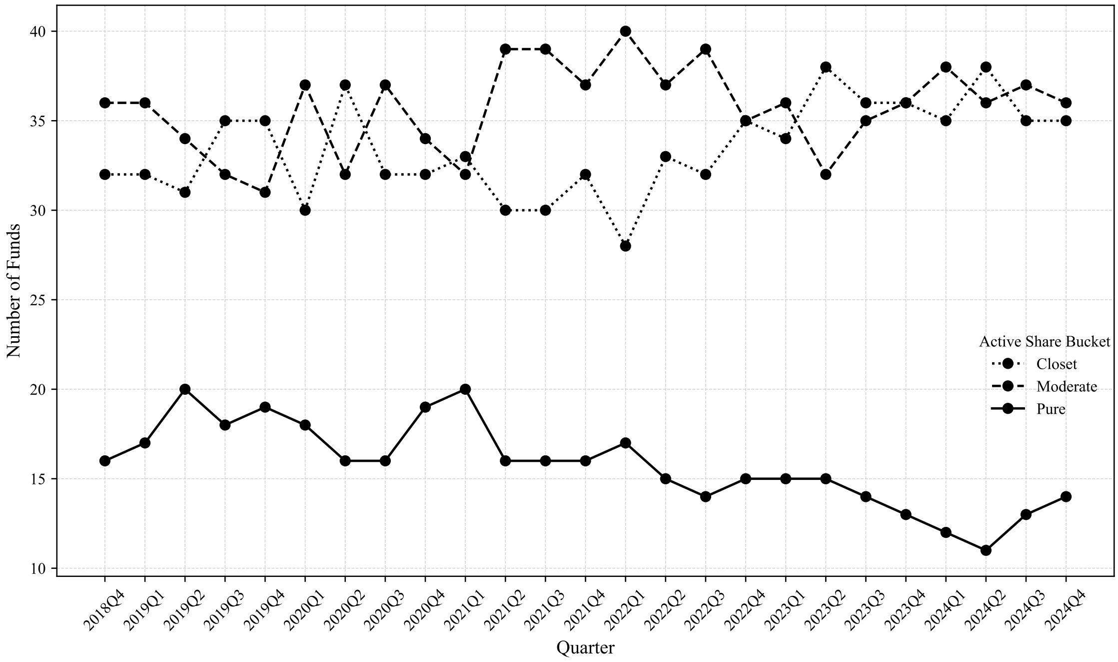

Figure A.3

Number of Funds by Active Share Group Over Time.

This figure tracks the number of funds in each Active Share category (Closet, Moderate, Pure) across all quarters from 2018Q4 to 2024Q4. It provides insight into the evolution of fund composition over time.

AI appendix

We have employed ChatGPT and Grammarly for help with coding and grammar.