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# Is There Skill Among Norwegian Fund Managers?

*An Empirical Analysis of Managerial Skill in Active Fund Management*

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# Abstract

In this study, we examine the ability of Norwegian actively managed mutual fund managers in identifying and exploiting market mispricing. We find that fund managers exhibit skill in identifying and capturing mispricing in the market, using last periods trading activity as a predictor of subsequent periods returns. A one standard deviation increase in turnover, results in an increase in annual expected excess return from 1.37% to 2.08%. Funds investing in multiple markets display greater levels of skill than those investing in a single market, with funds investing in a single market having a shorter profit realization from trading, compared to funds investing in multiple markets. We find that smaller funds, as well as those investing primarily in mid-cap stocks, display superior skill relative to the rest. In addition, we identify that fund managers, conditional on where they invest, are driven by different factors, with multi-area funds trading on increases in liquidity, whereas single-area funds increase trading in response to a reduction in market distress risk.


***Keywords*** – Trading Activity, Norwegian Mutual Funds, Skill

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# 1 Introduction

This paper examines whether Norwegian actively managed mutual funds exhibit skill. This is an important question, as a lack of skill would render the existence of these funds redundant. A common argument for the existence of actively managed funds, is their role in price discovery and in correcting market mispricing, a role that in turn leads to more efficient markets (Kacpercyk & Seru, 2007). Our study is closely related to the study by Ľuboš Pástor and Taylor (2017), where a new method of identifying skill in active fund management is proposed and applied to a sample of U.S. mutual funds.

To answer the question of skill in Norwegian funds, we first present a model[1] that, given the assumption of time-varying profit opportunities, demonstrates how the turnover (trading activity) of funds in response to these, is directly tied to skill. We use a sample of 216 actively managed Norwegian mutual funds investing exclusively in equity, including both operational and discontinued funds, ensuring a sample free of survivorship bias in the period 2000-2022. Our study has two main findings, the first being that actively managed Norwegian mutual funds exhibit significant levels of skill in the period 2000-2022. The second main finding is that funds investing in a single-country, exhibit a unique turnover-performance relationship, where the profit from trades are realized to a higher degree in the same period as the trades occur.

Performing four panel data regressions with different specifications, we find supporting evidence for the strongest relationship between skill and performance being present in the time-series, where turnover from the previous period ($t-1$) is the independent variable and benchmark-adjusted return (at time $t$) is the dependent variable, effectively making turnover a good predictor of a subsequent period's excess return. The main results, do however, show a slight indication of aggregate variables confounding the estimates in our sample.

After identifying the existence of skill, we analyze how performance varies across fund characteristics in the cross-section, where we group funds by their investment style and size, before examining what characterizes the funds that exhibit the most skill in the time-series. We use a formalized relationship between the cross-sectional and time-series

[1] As first proposed by Ľuboš Pástor and Taylor (2017).

coefficients, to based on characteristics, predict which fund groups are expected to show the strongest skill in the time-series. We find varying degrees of this relationship's ability to predict skill in the time-series, given cross-sectional values. We find that skill level is increasing with decreasing fund size, with small funds exhibiting the highest skill level. Additionally, we find that funds holding mainly growth- or value-stocks exhibit higher skill than those holding a combination. For stock size category, funds holding mid-cap stocks display higher levels of skill, compared to small- and large-cap.

Next, we group funds based on whether they invest in a single or multiple areas[2]. When performing a turnover-performance regression analysis, we find that multi-area funds exhibit a higher level of skill compared to single-area. However, when we use $\text{turnover}_t$ instead of $\text{turnover}_{t-1}$ as a predictor of returns, we find that single-area funds exhibit higher skill than with $\text{turnover}_{t-1}$. We theorize that this is a consequence of single-area funds having a shorter trade/profit relationship than multi-area funds, which results in the main portion of their payoff from a trade happening in the same period as the trade itself. We go on to examine the characteristics of single-area funds in terms of stock holdings and size, and here, observe characteristics that support the observed horizon dynamics.

After establishing skill, and how it varies conditional of fund style, size, and investment area, we go on to explain drivers of turnover for individual funds and for the aggregate market. Using the funds from the two investment areas with the most funds in our sample, Global and Norway, as proxies for multi- and single-area funds, we apply four mispricing proxies in explaining turnover. For funds with a multi-area investment strategy, turnover on aggregate, is driven by an increase in market liquidity, decreased sentiment, and high distress risk. For single-area funds, managers are driven by lowered distress risk and increased volatility.

## 1.1 Literature Review

Previous studies have examined the relationship between the trading activity of actively managed mutual funds and its effect on returns. Existing studies employ different methodologies for examining the relationship, yielding mixed results.

[2] Where "area" refers to distinct geographical markets.

### 1.1.1 U.S. Literature

Champagne et al. (2017) propose a modified turnover measure that calculates turnover as the proportion of the portfolio that changes between consecutive quarters. The study reveals that an increase in turnover predicts a negative effect on subsequent return, implying that increased trading activity destroys value for investors. Champagne et al. (2017) investigate the relationship through a cross-sectional analysis and use a sample of 2856 mutual funds based in the United States from 1991 to 2001.

Cremers and Petajisto (2009) introduce a metric called "Active Share" which quantifies the level of activity as the proportion of portfolio holdings that deviate from the benchmark index holdings. A significant finding is that funds with the highest Active Share show greater returns than their benchmarks, both pre and post expenses. Funds with a high active share exhibit persistence in performance, indicating that their active management strategies are consistent in generating value over time. This study covers a sample of 2647 U.S. based mutual funds from 1980 to 2003.

A study by Amihud and Goyenko (2013) uses $R^2$ as a measure of trading activity. By regressing fund returns against a multi-factorial benchmark model, Amihud and Goyenko (2013) find that returns can be predicted by the level of $R^2$. A low $R^2$ suggests a high level of turnover that deviates from the benchmark and serves as a predictor of increased fund performance. This implies, similarly to the findings of Cremers and Petajisto (2009), that higher trading activity and stock selection are positively related to mutual fund performance.

Fama and French (2010) emphasize on the difficulty in distinguishing skill from luck. They find that, when studying active funds in the aggregate, they closely resemble the market portfolio. By employing boot-strap simulations to evaluate fund performance, their findings indicate that only a small number of funds generate benchmark-adjusted expected returns that are sufficient to offset their expenses. The overall effect of increased trading activity on returns is not consistently positive, as Fama and French (2010) underline that there are cost differences between index funds and actively managed funds.

### 1.1.2 Norwegian Literature

There is limited research examining the relationship between the trading behavior and performance of active Norwegian mutual funds. There are, however, studies that examine other factors related to the performance of Norwegian funds. A study by Høiberg (2020) examines the effect of scale on fund performance. Høiberg (2020) finds results indicating that both small and large funds exhibit lower performance, compared to medium-sized funds. On average, the performance deteriorates as fund size increases. The sample is comprised of 49 funds over a time period from 2005 to 2018.

Gjerde and Sættem (1991) examine the relationship between managerial skill and mutual fund performance in the Norwegian market. They discover that fund managers exhibit skill in their ability to time the market, but display little proficiency in picking individual stocks. When examining Norwegian mutual funds between 1980 and 1990, they find that all funds in the sample outperform the market on a risk-adjusted basis in the sub-period between 1982 and 1984. In terms of gross returns however, no funds exhibit persistence in outperforming the market in any three-year period.

# 2 Data

The following section describes how funds are selected for the study, what data material is required, and the descriptive statistics and structure of the data. Our study relies primarily on data from Morningstar Direct, a comprehensive investment analysis platform provided by Morningstar, Inc. The database offers time-series data on the turnovers, gross returns and benchmark returns of Norwegian funds, as well as other fund-specific variables.

Although the main analysis relies on data from Morningstar, we incorporate supplementary data from Bloomberg as we expand the study. We review all data for errors and irregularities, make adjustments as needed, and as an additional precaution for having missed any outliers, we Winzorise[3] all variables at the 1 % level.

## 2.1 Inclusion Criteria

Because our objective is to identify the level of skill in Norwegian actively managed mutual funds, we only seek funds that adhere to specific characteristics for the final sample, which we identify using specific search filters in Morningstar Direct. The initial criterion is that the funds' base currency be denominated in NOK, a condition that retrieves all funds that are domestic to Norway. In addition, we apply a filter that isolates actively managed funds, hence excluding index funds that lack inherent skill. To prevent the duplication of funds, a filter is applied that only includes the primary share class of each fund. The distinction between share classes primarily lies in the fee structure imposed on investors and the minimum investment amount required.

## 2.2 Gross Return

All available data on gross returns is collected for each fund with monthly observations. Morningstar Direct reports their calculation of gross returns as follows from equation 2.1:

$$GrossReturn_{i,y} = \left(\frac{TR_{i,y} + 1}{1 - RC_{i,y}}\right) - 1 \tag{2.1}$$

[3]Winsorizing is a technique where extreme values in a dataset are replaced with specific percentile values to reduce the impact of outliers.

$TR_{i,y}$ is the total return of fund $i$ in month $y$, while $RC_{i,y}$ represents the un-annualized representative cost that covers month $y$. The representative cost is a fee level that is adjusted for the fund's share class. The monthly gross return is calculated by dividing the total return by the adjustment, representing the amount an investor would earn before incurring any expenses.

## 2.3 Morningstar Category Index

Morningstar assigns each fund a Morningstar Category Index (MCI), which is a benchmark that is based on the fund's portfolio composition. We collect the monthly returns for all MCI indices and pair them with their respective funds. Further, we compute the monthly benchmark-adjusted returns (excess returns) by equation 2.2 where the excess return, denoted as $R_{i,y}$, is computed for all funds $i$ for each month $y$, by subtracting the monthly benchmark return $MCI_y$ from the funds gross return $GrossReturn_{i,y}$.

$$R_{i,y} = GrossReturn_{i,y} \text{ - } MCI_y \tag{2.2}$$

## 2.4 Turnover

We obtain the funds' turnover ratios from Morningstar Direct, which are reported every fiscal-year, meaning that for Norwegian funds, turnovers are based on trade volumes from January to December. Turnover ratios are calculated for each fund $i$ in each year $t$, as follows from equation 2.3, as the lesser of sales and purchases in a given year ($t$), divided by the fund's annual average total net assets.

$$Turnover_{i,t} = \frac{\text{min(buys, sells)}}{\text{avg(TNA)}} \tag{2.3}$$

Turnover, given by equation 2.3, is an effective measure of trading activity that is not a consequence of rebalancing, as it is largely immune to transactions that result from investor in- and out-flow. Investors buying shares in a fund causes an in-flow of capital, which the fund uses to buy stocks. Conversely, out-flow is caused by existing investors selling shares, pulling capital out of the fund, forcing the fund to sell their holdings. The resulting rebalancing from investor flow has an equal effect on both the numerator and denominator of the turnover in equation 2.3, immunizing the turnover ratio against non-strategic trading activity caused by rebalancing.

## 2.5 Descriptive Statistics

For a fund to be included in the sample, we require both the excess returns and turnovers to be available as complete observation pairs, meaning that absence of either one in a given month, will yield a missing observation. This is a reoccurring issue in our data, as we have extensive data available on gross- and benchmark returns but have limited data on turnover.

We have a total of 30,275 observations of excess returns, and 23,172 observations of turnover. The resulting sample is, due to missing data on turnover, restricted to a size of 23,172 complete observation pairs of excess return and turnover. Descriptive statistics of the final sample are illustrated in table 2.1.

**Table 2.1:** Descriptive Statistics

Table 2.1 shows descriptive statistics of the variables obtained from Morningstar direct after omitting incomplete observation pairs of excess returns and turnover. The excess returns are the funds' gross returns subtracted by their assigned Morningstar Category Index (MCI) benchmark returns. Means and standard deviations (Std.Dev.) are in %.

| Variable | Obs. | Mean | Std.Dev. | Min | Max |
|---|---|---|---|---|---|
| Turnover | 23172 | 64.050 | 71.230 | 0.000 | 395.000 |
| Gross Return | 23172 | 0.968 | 4.627 | -13.750 | 12.510 |
| MCI Return | 23172 | 0.847 | 4.459 | -15.300 | 13.510 |
| Excess Return | 23172 | 0.135 | 1.911 | -5.514 | 6.108 |

Table 2.2 shows the distribution of observations throughout the time-range of the sample. The sample is restricted to the time period of 2000 to 2022, which is a result of data on turnover being nonexistent prior to 2000 in the Morningstar Direct database.

**Table 2.2:** Descriptive Statistics for Sub-Periods

Table 2.2 shows means and standard deviations (Std.Dev.) for benchmark-adjusted (excess) returns and turnover in four time intervals. The two left columns denote the time intervals and the number of observations within each interval. Means and standard deviations for excess returns and turnover are shown in columns 3-4 and 5-6, respectively, where values are reported in %.

| | | Excess return | | Turnover | |
|---|---|---|---|---|---|
| Interval | Obs. | Mean | Std.Dev. | Mean | Std.Dev. |
| 2000 - 2007 | 413 | 0.997 | 2.326 | 69.661 | 72.918 |
| 2008 - 2012 | 4909 | 0.189 | 1.951 | 84.193 | 78.949 |
| 2013 - 2017 | 4066 | 0.151 | 1.739 | 58.395 | 58.685 |
| 2018 - 2022 | 3315 | 0.119 | 2.072 | 67.208 | 92.629 |

The use of monthly excess returns with annual turnovers has structural implications for the data. $y \in \{1, 2, ..., 12\}$ for each year ($t$), meaning that the benchmark-adjusted return for fund $i$ in a given month-year can be denoted as $R_{i,y,t}$. Because the turnover is equal for all months ($y$) within a year ($t$), the month subscript is removed from turnover, denoting the turnover for a fund in a given year as $Turnover_{i,t}$. The data structure when pairing the benchmark-adjusted returns $R_{i,y,t}$ with the turnover ($Turnover_{i,t}$), is visualized in table 2.3, where turnovers for fund $i$ are equal within each year ($t$).

**Table 2.3:** Data Structure

Table 2.3 visualizes the data structure when pairing monthly benchmark-adjusted (excess) returns with annual turnover. Turnover is equal for all months $y$ within a given year $t$. The table illustrates that in a given year $t$, the excess return $R_{i,y,t}$ for a fund $i$ changes with every month $y$, while the turnover remains the same.

| Month | Excess Return | Turnover |
|---|---|---|
| 1 | $R_{i,1,t}$ | $Turnover_{i,t}$ |
| 2 | $R_{i,2,t}$ | $Turnover_{i,t}$ |
| 3 | $R_{i,3,t}$ | $Turnover_{i,t}$ |
| ... | ... | ... |
| 12 | $R_{i,12,t}$ | $Turnover_{i,t}$ |

# 3 Model Proposition

In the following section, we introduce a model first presented by Ľuboš Pástor and Taylor (2017) that ties turnover to performance in the presence of profit-opportunities, and establish why this relationship identifies skill. In 3.1 we present the dynamics and underlying model assumptions, and why the relationship is best observed in the time-series. Next, in 3.2, we show why the relationship between turnover and performance is present in the cross-section. We then, in 3.3, use the model established in 3.1 to simulate profit opportunities and their effect on the turnover response, which we in 3.4, with an extension for sub-optimal trading, use to visualize how different levels of skill, affect the slope that identifies skill in the time-series relation.

## 3.1 Model Dynamics

The first assumption in the model is that there are time-varying profit opportunities in the market. With time-varying profit opportunities in the market, a fund can capitalize on these by buying or selling shares. With increased trading, turnover increases. The assumption of profit opportunities, means the profit function can be expressed as a function of turnover:

$$P(X_t) = \pi_t X_t^{(1-\theta)} \tag{3.1}$$

Where $\pi_t$ are the profit opportunities at time $t$, $X_t$ being the turnover at time $t$, and $\theta$ a constant with properties $0 < \theta < 1$, and $\pi_t \geq 0$. The term $(1-\theta)$ captures a key economic principle that, although profits may initially rise in tandem with increased turnover, there exists a diminishing marginal return on profits as turnover increases. This concave relationship in the turnover exponent $(1-\theta)$ , provides a realistic constraint. It implies that while turnover facilitates profit realization, the efficiency of this conversion lessens, as the fund engages in more frequent trading. A larger $\pi_t$ makes funds' profit-opportunities higher.

Next is the cost associated with trading, which can also be expressed as a function of turnover:

$$C(X_t) = cX_t^{(1+\gamma)} \tag{3.2}$$

$c$ is a positive constant that scales with the cost level, and $\gamma$ defines the curvature of the cost function. The parameter $\gamma$ determines the degree to which the cost function is convex and has the property that $\gamma \geq 0$. The justification for the convexity lies within the findings of Kyle and Obizhaeva (2016), in that the cost associated with trading a particular stock, increases at an accelerating rate with the volume traded, which is reflected in the convex nature of $C(X_t)$. The idea is that, as more of a single stock is traded (i.e., $X_t$ rises), the liquidity constraints and the costs of market impact[4] increase disproportionately, hence the convex shape of the function.

The behavior of $C(X_t)$ can vary depending on the nature of trading. If a higher $X_t$ is due to trading larger quantities of individual stocks, then a pronounced convexity (a larger $\gamma$) is expected. However, if an increase in $X_t$ is due to the fund diversifying its trades across a broader range of stocks, rather than concentrating volume in specific stocks, then the cost function should approximate linearity that is, $\gamma$ should be near zero. This aligns with a market environment characterized by widespread mispricing, where profit opportunities are distributed across various securities, leading funds to trade across a broader portfolio, rather than concentrating on large positions in a few securities. Ľuboš Pástor and Taylor (2017) find that $\gamma = 0$ in their study, a finding we extend to our model.

Given the assumption that a fund seeks to maximize their after-cost profits, the objective function for the optimal level of turnover is:

$$\max\left[P(X_t) - C(X_t)\right] \tag{3.3}$$

Substituting in 3.1 for $P(X_t)$ and 3.2 for $C(X_t)$, and solving for the optimal level of turnover ($X_t^*$) gives the expression:

$$X_t^* = \left(\frac{\pi_t(1-\theta)}{c(1+\gamma)}\right)^{\frac{1}{\theta+\gamma}} \tag{3.4}$$

From 3.4 we can see that the optimal turnover falls as costs ($c$) increase, while optimal turnover increases for higher profit opportunities ($\pi_t$). Assuming $X_t = X_t^*$.[1][5] and solving for $\pi_t$ in equation 3.4 , we derive an expression for $\pi_t$ in terms of turnover $X_t^*$. This

[4]The change in the price of a stock from trading large quantities of it.

[5]i.e., That funds have optimal turnover in response to profit opportunities.

expression is then substituted back into equation 3.1. This substitution allows us to reformulate the profit function $P(X_t)$, now directly relating it to the turnover level $(X_t)$, effectively transforming the original profit function into the form presented in equation 3.5, which gives the time-series relation of profit, in the presence of profit opportunities, expressed as a function of turnover:

$$P(X_t^*) = \frac{c(1+\gamma)}{1-\theta} (X_t^*)^{(1+\gamma)} \tag{3.5}$$

A funds realized return in period $t+1$ $(R_{t+1})$, is then derived from the profit function (3.5) and the cost function (3.2). It is calculated as the profit $P(X_t^*)$ from the optimal turnover in period $t$, adjusted for the trading costs $C(X_{t+1}^*)$ in period $t+1$. This insight is important, as it establishes how returns in period $t+1$ are achieved from the realization of profit opportunities from time $t$ and reduced by the trading costs incurred from the trading of profit opportunities at time $t+1$.

$$R_{t+1} = \frac{c(1+\gamma)}{1-\theta}(X_t^*)^{1+\gamma} - c(X_{t+1}^*)^{1+\gamma} + \eta_{t+1} \tag{3.6}$$

The term $\eta_{t+1}$ represents the mean-zero deviation of the actual profits from the expected profits. The inclusion of $\eta_{t+1}$ acknowledges the inherent uncertainties in financial markets, capturing the unpredictable variations that affect the returns of a fund.

Ľuboš Pástor and Taylor (2017) also assume that the profit opportunities are varying over time, in a way that allows the conditional mean of $(X_{t+1}^*)^{1+\gamma}$ given $X_t^*$, to be estimated as:

$$E((X_{t+1}^*)^{1+\gamma}|X_t^*) = \mu(1-\rho) + \rho(X_t^*)^{1+\gamma} \tag{3.7}$$

This assumption requires that profit opportunities in a given period are dependent on the previous period. In the context of the model, the autoregressive nature of profit opportunities is crucial for the conditional mean to hold. The autoregressive behavior ensures a level of predictability and stability in the profit opportunities over time, allowing for the use of past data to forecast future values. Continuing the assumption of $\gamma = 0$, and $\mid \rho \mid < 1$, with $\rho$ defined as the autocorrelation of $X_t^*$, we get:

$$\mu = E(X_t^*) \tag{3.8}$$

Hence, the turnover-performance relationship is, under these assumptions, accurately described by the function:

$$R_{t+1} = a + bX_t^* + \epsilon_{t+1} \tag{3.9}$$

Where

$$a = -c(1-\rho)E(X_t^*) \tag{3.10}$$

And

$$b = \frac{c}{1-\theta} - \rho \tag{3.11}$$

Given

$$E(\epsilon_{t+1} | X_t^*) = 0 \tag{3.12}$$

The economic insight we get from the preceding model, is how the dynamics of a time-difference between the profit opportunities, the associated trading cost from executing trades based on these opportunities, and the subsequent time delay before the profits are realized, makes the time-series relation between turnover and performance stronger than the cross-sectional. The key distinction between the time-series and the cross-section is how trading costs can be seen in the right context. In the time-series, costs from trading in period $t+1$ can be isolated in the intercept ($a$) in 3.10, isolating the cost from trading in period $t$ that is responsible for the subsequent profit in $t+1$ in the slope from 3.11 ($b$). Correctly assigning trading and its associated costs with subsequent periods returns, under the model assumptions, enables a more precise identification of skill.

## 3.2 Time-Series Versus Cross-section

Ľuboš Pástor and Taylor (2017) take the unconditional expectation of 3.9, using equation 3.10 and 3.11 to get the turnover-performance relation in the cross section:

$$E(R_t) = hE(X_t^*) \tag{3.13}$$

Where

$$h = \frac{c\theta}{1-\theta} \tag{3.14}$$

As we argue in 3.1, the cross-sectional relationship does not take the timing of the costs into consideration. To illustrate this, Ľuboš Pástor and Taylor (2017) take the difference in slopes between the time-series coefficient ($b$) in 3.11 from equation 3.9, and the cross-sectional slope ($h$) in 3.14 from 3.13, which gives the relationship between the two:

$$b - h = c(1-\rho) \tag{3.15}$$

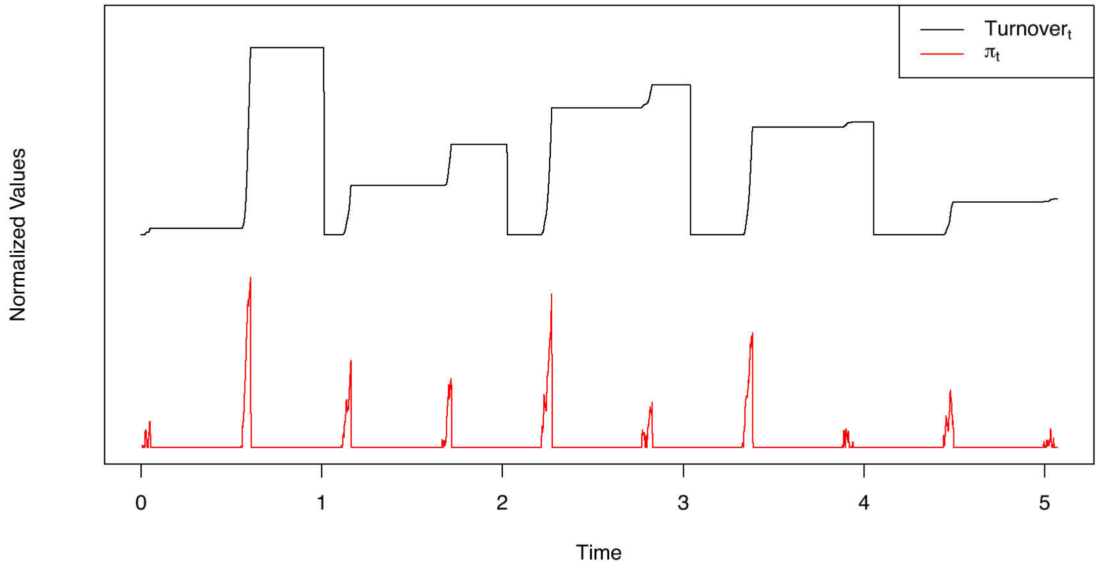
Where the slope in the cross-section ($h$) will be weaker because the costs incurred from increasing turnover in a period immediately subtract from a funds return in the same period. Assuming that $c$ and $\theta$ in 3.13 are equal across funds, the slope $h$ is the same for all funds.

## 3.3 Model for Time-Varying Profit Opportunities

We simulate profit opportunities that follow a stochastic process with periodic peaks. An initial occurrence of profit opportunities has an autocorrelated movement with an added noise term. Combining time-varying profit opportunities with the optimal turnover response in equation 3.4, the dynamics of optimal trading are illustrated in figure 3.1, where turnover resets to 0 for each new time interval ($t$):

**Figure 3.1:** Optimal Turnover Response to Profit Opportunities

The figure illustrates the dynamics of the optimal level of turnover ($X_t^*$) for a fund in response to profit opportunities. The black line shows the level of turnover, and the red line shows the frequency and magnitude of time-varying profit opportunities ($\pi_t$). Turnover is cumulative within each $t$, as indicated by the x-axis denoted "Time".




From equation 3.1, the dynamics between turnover and profit opportunities illustrate the linearity under the parameter assumptions made in 3.1 between trading and profit opportunities. This is important, as it demonstrates that turnover from model 3.4 with optimal trading, in response to profit opportunities, is scaled by the magnitude of $\pi_t$, the cost constant ($c$) and the diminishing return ($\theta$) from acting on these trades.

## 3.4 Sub-Optimal Trading

With the introduction of sub-optimal trading, the relationship between turnover and skill weakens both in the time-series and in the cross-section. The time-series is given by the following equation:

$$R_{t+1} = \hat{a} + \hat{b}X_t + \epsilon_{t+1} \tag{3.16}$$

Where

$$\hat{a} = -c(1-\rho)E(X_t) \tag{3.17}$$

And

$$\hat{b} = c\left[\frac{1-\theta(1-\delta)}{1-\theta} - \rho\right] \tag{3.18}$$

Where the difference in model 3.16, compared to model 3.9, is in coefficient $\hat{b}$, from the introduction of the parameter $\delta$. This parameter ($\delta$) represents the level of skill, with skill being defined as the degree to which a fund manager can identify and successfully capture the time-varying profit opportunities. For any level of $\delta < 1$, the relationship between performance and turnover weakens, both in the time-series and the cross-section. $\hat{b}$ with $\delta = 1$ in 3.16 becomes identical to $b$ in 3.6.

Combining our simulation of time-varying profit opportunities in 3.3 with varying levels of skill, in the form of $\delta$, we demonstrate the weakening(strengthening) of the $\hat{b}$ coefficient in the time-series for differing levels of $\delta$.

**Figure 3.2:** Varying Levels of Skill in the Time-Series

The figure shows the simulated development of fund value in the presence of profit opportunities for funds with different levels of skill ($\delta$). The lines with different values of $\delta$ illustrate how varying levels of skill affect development in fund value through time, when exposed to identical market shocks (hence the positive drift). Time-varying profit opportunities of different magnitudes are represented by the black line ($\pi_t$).

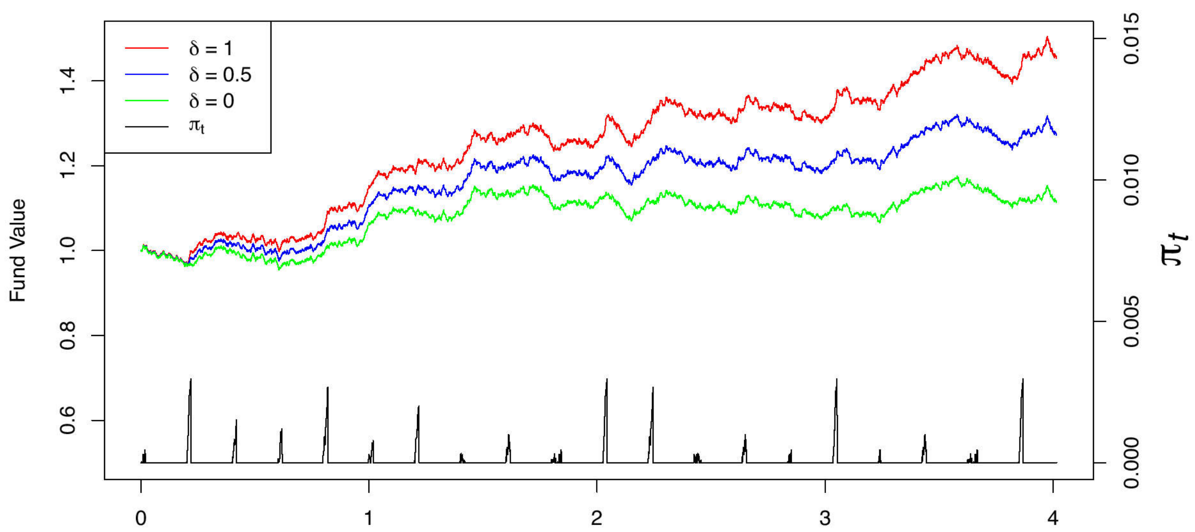



Figure 3.2 demonstrates how varying levels of skill ($\delta$) for a fund will impact its returns in the time series. The figure represents before benchmark-adjusted returns, which is why no skill ($\delta = 0$) demonstrates a positive drift and can be thought of as the benchmark. The difference between the green line ($\delta = 0$) and the other colored lines (blue and red), will as seen in equation 3.16, as long as $\delta > (\rho - 1)(1 - \theta)/\theta$.[2][6], give a positive slope ($\hat{b}$) in the time-series.

[6] Given $(\rho - 1)(1 - \theta)/\theta > 0$

In the cross-section, the level of skill ($\delta$) has the same effect as in time-series, with the slope being:

$$\hat{h} = \frac{\delta\theta}{1-\theta} \tag{3.19}$$

Hence, the difference between the two slopes will remain identical to the difference with optimal trading[7]:

$$\hat{b} - \hat{h} = c(1-\rho) \tag{3.20}$$

[7] Given the same assumptions as in 3.2.

# 4 Methodology

In the following section we present the linear regression model and its specifications, that will be applied in the empirical analysis in section 5. From the model proposition in section 3, we find from equation 3.9 for optimal trading and 3.16 with sub-optimal trading, how the time-series relation is the preferred method to examine the relationship between turnover and return, to identify skill among fund managers. We first present the general regression model and how adding different fixed-effects specifications to it, will enable identification of skill, before discussing treatment of error terms.

## 4.1 Regression Model

Equation 4.1 presents the regression equation derived from the model proposed in equation 3.9. Additional restrictions and specifications are detailed in sections 4.2.1 and 4.2.2 for entity- and time-fixed effects respectively.

$$R_{i,y,t} = a_i + b_i X_{i,t-1} + \epsilon_{i,y,t} \tag{4.1}$$

The dependent variable $R_{i,y,t}$ is the excess return[8] for fund $i$ in month $y$ in year $t$. By adjusting returns using the Morningstar assigned benchmark (MCI) as opposed to using the primary prospectus benchmark[9] (PPB), is that the MCI is based on the fund's actual holdings. Benchmarks assigned by the funds themselves are prone to manipulation by fund managers, choosing a benchmark that is not representative of the funds risk-profile or investment strategy, but one that is easier to beat (Sensoy, 2009). As a consequence, the MCI assigned by Morningstar is a more objective benchmark, yielding an excess return that is more accurate and accounts to a higher degree for the funds risk-profile and investment strategy. In the regression model in equation 4.1, $a_i$ is the intercept of the regression line for fund $i$, where with no fixed effects, we impose the restriction that:

$$a_1 = a_2 = ... = a. \tag{4.2}$$

[8] i.e., in excess of its benchmark defined in section 2.3.

[9] The benchmark chosen by the fund.

With restriction 4.2, the model assumes an intercept that is constant across all funds. A model specification where $a_i$ is pooled for all funds $i$ does not control for unobserved heterogeneity across funds, or time.

The $b_i$ term in 4.1 is the slope of the return-turnover relationship for fund $i$. The slope represents the linear line that best fits the data and shows how much the dependent variable is expected to increase (or decrease) when the independent variable increases by one unit. In analysis of the full sample, we pool $b_i$ for all funds imposing the restriction:

$$b_1 = b_2 = ... = b. \tag{4.3}$$

Imposing restriction 4.3 in the linear model assumes that the coefficient $b_i$ in 4.1 is constant for all funds. When analyzing differences in attributes between funds, $b_i$ is pooled conditional on these categories.

The explanatory variable $X_{i,t-1}$, is the turnover of fund $i$ from the previous year $(t-1)$. The use of lagged turnover $(X_{t-1})$ is extensively discussed in the model proposition in section 3.

The error term $\epsilon_{i,y,t}$ in equation 4.1 captures the unexplained variance in excess returns, which remains after accounting for the influence of previous periods turnover.

## 4.2 Panel Data

It is apparent from equation 3.9 in section 3 that the estimation problem can be treated as a panel data regression, as the relationship between turnover and performance as shown in section 3.2 should be, if present, identifiable both in the cross-sectional and the time-series dimension[10]. The use of panel data allows for simultaneous examination of both time-series and cross-sectional aspects of the data. Applying entity-fixed effects controls for idiosyncratic variation across entities, while time fixed-effects control for temporal dynamics in the data.

[10]Albeit stronger in the time-series.

We apply fixed-effects specifications to our panel data regressions, identical to those used by Ľuboš Pástor and Taylor (2017), which allows for comparison of the main results. The entities of our panel are funds denoted by $i$, while the time dimension is denoted by $y, t$, where there are 12 months $y$ for each year $t$. We have an unbalanced panel with an unequal number of observations for each fund. We describe how to account for weighting issues that accompany an unbalanced panel in section 4.2.1.

### 4.2.1 Fund Fixed Effects

With fund fixed effects, we do not impose the restriction in equation 4.2 and instead allow a distinct intercept $a_i$ for each fund. This is crucial, as we see in equation 3.9 within the framework of the model, that holding $a_i$ separate allows for the cost from this period's turnover, to be captured by the intercept, thereby isolating the correct cost with the correct profits in coefficient $b$. This is why fund-fixed effects is the main specification added to our regression model in 4.1, and that the resulting coefficient ($b$) is a direct measure of skill. Apart from the modelled relationship between turnover and performance in section 3.1, in econometrics, the use of fund fixed effects allows for the control of unobserved fund-specific characteristics, by assuming that there is an inherent time-invariant heterogeneity between funds.

This specification, controls for the idiosyncratic attributes within funds that may create a bias in the performance-turnover coefficient $b$, by letting these factors instead be captured by the intercept. The fund-specific attributes in question might include[11] investment strategy/philosophy, risk appetite and sector focus. It is reasonable to assume that these characteristics will remain relatively stable over time, and that the benchmark-adjustment of returns will capture time-variant changes between funds within the same sector.

The use of fund fixed effects also has the added benefit of a more intuitive coefficient interpretation, giving the results of the regression output as the average turnover-performance coefficient $b$, weighted based on the number of observations each fund $i$ has in the sample period. This relative weighting ensures that the findings are not skewed by funds that are under- or over-represented in the data[12].

[11] Not an exhaustive list.

[12] See Appendix B, p. 1521 in Ľuboš Pástor and Taylor, 2017 for detailed analysis and proofs.

### 4.2.2 Time Fixed Effects

Time-fixed effects are useful because they allow controlling for variations that are consistent across funds but vary over time. The use of time fixed effects adds a control variable $\gamma_{y,t}$ to the general regression model in equation 4.1, and provides an extended model seen in equation 4.4. In the regression where only time-fixed effects are applied, the $\gamma_{y,t}$ is time-variant for all $y, t$.

$$R_{i,y,t} = a_i + b_i X_{i,t-1} + \gamma_{y,t} + \epsilon_{i,y,t} \tag{4.4}$$

The inclusion of the time component $\gamma_{y,t}$ controls for broader market influences that have the same impact on all funds. Examples of market-wide influences are macroeconomic shocks, policy changes, recessions, and booms. These are effects that create noise and confound the turnover-performance relationship, if not accounted for. The main argument as to why it is not appropriate to use time-fixed effects in our main analysis, is from the model dynamics in equation 3.9, that demonstrate the importance of unique $a_i$ for funds, in order to correctly assign costs from trading. Using only time-fixed effects assumes the same $a_i$ for all funds, which according to the model and equation 3.9, makes the timing of cost irrelevant, making the specification purely cross-sectional, which as we argue in section 3.2 will yield a weaker relationship to skill[13]. Additionally, our dependent variable $R_{i,y,t}$ in equation 4.1, being benchmark-adjusted returns, we argue that the time variation of interest is captured by this variable. Since funds with similar holdings will share the same benchmark, returns will effectively control for time-varying changes that effect funds sharing the same benchmark. Adding time-fixed effects controls for changes in turnover that come as a consequence of e.g., regulatory changes, or market changes that significantly influence trading activity across all funds. We test the turnover-performance relationship with time-fixed effects to examine the impact it has on the empirical findings.

[13] Given that skill is present.

### 4.2.3 Fund and Time Fixed Effects

The combined use of time- and fund-fixed effects controls for idiosyncratic fund characteristics and the effects of market-wide influences simultaneously. The specification for both fixed effects, is the regression in equation 4.4 with control for time-fixed effects ($\gamma_{y,t}$), not imposing the restriction in equation 4.2 enabling unique intercepts $a_i$ for each fund. When controlling for the noise created by entity- and time effects described in sections 4.2.1 and 4.2.2 respectively, the resulting estimate $b$ of the turnover-performance relationship is controlled for both time-effects (cross-sectional variation) and within-fund variation (heterogeniety).

## 4.3 Standard Errors

Funds within the same sector having the same benchmark adjusting their return, may cause correlations in the error terms that are systematic over time or between funds. This could lead to issues of autocorrelation and heteroskedasticity in the error terms, potentially resulting in inefficient standard error estimates and biased inferential statistics. To address these potential issues, we cluster standard errors both by time and by sector. Time clustering is used to correct for autocorrelation and external systematic shocks, that could uniformly affect all funds over time. We also cluster on MCI[14] to control for within-sector correlation of error terms, recognizing that funds within the same sector (MCI) may be subject to similar unobserved influences or exhibit correlated trading behaviors. The twofold clustering strategy aims to ensure that our standard error estimates are robust to both time- and sector-specific heteroskedasticity, thereby enhancing the reliability of our statistical results.

[14] Morningstar Category Index.

# 5 Empirical Results

In the following section we present our main results, identifying skill among Norwegian funds, and compare our findings to those by Ľuboš Pástor and Taylor (2017) looking at U.S funds. In section 5.2, we identify attributes that characterize funds that exhibit skill, first in terms of a funds stock holdings and size in 5.2.1, before examining levels of skill conditional on whether a fund follows a multi-area or single-area investment strategy in 5.2.2.

## 5.1 Main Results

**Table 5.1:** Turnover-Performance Regressions

The table shows the regression outputs of the Turnover-Performance relationship with four different specifications. The dependent variable is the benchmark-adjusted return for fund $i$ at time $t$. The independent variable is turnover for fund $i$ at time $t-1$. Model (1) is a linear model with no fixed effects. Model (2) has fund-fixed effects. Model (3) has month-fixed effects. Model (4) has both fund- and month-fixed effects. T-statistics are enclosed by () below coefficients.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | *Benchmark-Adjusted Return* | | | |
| | (1) | (2) | (3) | (4) |
| $Turnover_{t-1}$ | 0.00084** | 0.00182*** | 0.00063* | 0.00095** |
| | (2.29) | (2.77) | (1.95) | (2.04) |
| Month fixed effect | No | No | Yes | Yes |
| Fund fixed effect | No | Yes | No | Yes |
| Observations | 20,299 | 20,299 | 20,299 | 20,299 |
| *Note:* | | *p<0.1; **p<0.05; ***p<0.01 | | |

With four different specifications, we find a significant and positive relationship, which identifies skill among Norwegian actively managed mutual funds. In the presence of time-varying profit opportunities, skilled managers will capture these and earn in excess of their benchmark, with the result being strongest in (2).

In (1), not specifying any fixed effects, we observe a positive relationship between return and turnover. This shows that there is an inherent positive relationship on average, between the performance and turnover for Norwegian-based actively managed mutual funds. Such a relationship indicates that funds with higher turnovers, tend to achieve better performance.

The findings with fund fixed effects (2), which adjust for individual fund characteristics that remain constant over time, are in line with the model of time-varying profit opportunities presented in section 3, where we show in equation 3.9 how the turnover-performance relation is best captured in the time-series, which our results also suggest. This is one of the main findings of our thesis and it is both highly statistically significant and of economic significance. The findings are of importance because it confirms turnover as a predictor for subsequent returns in period $t$.

In our sample, the average within-fund standard deviation of turnover ($X_{i,t-1}$), is 0.326. Concurrently, the annual average benchmark-adjusted return ($R_{i,t}$) is 1.37%. Based on the regression coefficient from (2), a one standard deviation increase in turnover is associated with an increase in the expected annual return of 0.71%. The calculation for this increase is given by the product of the coefficient for turnover from our model (0.00182), the standard deviation of turnover (0.326), and the annualization factor (1200), resulting in an expected annual return increase of 0.71%. This expected increase in return of $\approx 52\%$, indicates a substantial impact of turnover on fund performance, beyond the historic average of 1.37% annualized excess return[15].

With time fixed effects as specification in (3), the relationship between turnover and performance weakens compared to (2). The inclusion of time fixed effects accounts for time-varying factors such as market conditions or macroeconomic events. Since (3) is without fund-fixed effects, the coefficient is with purely cross-sectional specifications, as $a_i$ is averaged across funds. The statistical significance is also reduced to a t-statistic of 1.95. The coefficient in model (3) reflects a weighted average of period-by-period, cross-sectional regressions of the turnover-performance relationship. The positive and significant coefficient in (3), is in line with the model (equation 3.13), in that a relationship of skill, if present, also holds in the cross-section, but that the relationship is weaker.

With both fixed effects (4), the relationship between turnover and performance is still significant. This model offers the most comprehensive control for both time-varying and

[15] i.e., geometric return.

fund-specific factors. The robust positive coefficient underscores the assertion that actively managed mutual funds in Norway, when adjusting for both time-specific and fund-specific variations, tend to have a higher return as turnover increases. Thus, (4) suggests that even when accounting for cross-sectional and within-fund variation, the positive relationship between turnover and performance persists.

Utilizing the relationship between the time-series and the cross-section established in section 3.2, where the difference in slopes between the cross-section and the time-series is given by the relationship $b - h = c(1 - \rho)$, we calculate the implied $c$ for the funds in our sample. From table 5.2, the full sample average annual autocorrelation is 0.328. We can then from the time-series slope $b$ in (2) and the cross-sectional slope $h$ in (3) solve for implied $c$:

$$12(0.00182 - 0.00063) = c(1 - 0.328) \tag{5.1}$$

The average autocorrelation for the funds in our sample are in annual terms. We multiply the slopes by 12 to achieve the annual implied $c$ for the funds, which equates to an annual $c$ of 2.1%, which is a 21% higher $c$ than Ľuboš Pástor and Taylor (2017) who obtain a $c = 1.75\%$ for U.S mutual funds, suggesting that the cost of trading is significantly higher for Norwegian funds, which could be a consequence of the U.S funds being larger in size, enabling economies of scale (Investment Company Institute, 2023).

The coefficients from the four different outputs in table 5.1, when analyzing both the time-series and the cross-section are all positive, with (2) displaying superior slope and statistical strength. Purely controlling for cross-sectional variation in (3), dampens the slope of the coefficient in line with the relationship in equation 3.15. With two-way fixed effects in (4), the relationship between turnover and performance strengthens compared to (3), yet showing a significant fall compared to (2)[16]. Our results are also very similar to those found by Ľuboš Pástor and Taylor (2017), where our coefficients display the same dynamics in response to the application of the different specifications in table 5.1. In (2), the Norwegian sample displays an almost identical slope (0.00182) to that of U.S funds (0.00125). Our results differ in that, when accounting for two-way fixed effects (4), our slope is impacted to a large extent, suggesting that our observed relationship between turnover and performance could be confounded by aggregate variables, which is not an

[16]Both in coefficient and statistical significance.

effect observed by Ľuboš Pástor and Taylor (2017).

Our findings, and the implication they have for the role of active fund management is of importance. If funds managers correct for mispricing, they are effectively contributing to making markets more efficient, ensuring that resources are efficiently allocated. As a consequence, actively managed mutual funds play an important role in the economy, improving the amount of information reflected in exchange traded equities.

## 5.2 Fund Attributes: Impact on Performance

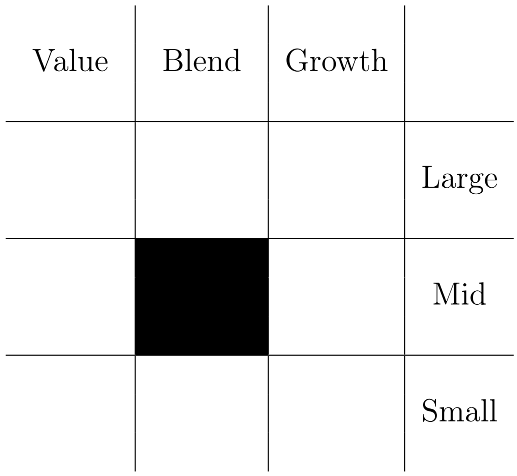
Next, we group funds by Morningstar Stylebox and size, and use summary table 5.2 to see how different attributes characterize performance over the sample period. We then tie the parameter values from each fund group to the relationship between the cross-section and the time series established in 3.15, which we use to predict which funds will perform best in the turnover-performance time-series relation. We then run regression model 4.1 for the fund groups to see how well the model predicts the turnover-performance relationship, and comment on findings. In section 5.2.2, grouping funds by whether they follow a single- or multi-area investment strategy, we examine the turnover-performance relationship conditional on investment area.

**Morningstar Style Box**

The Morningstar style-box (Morningstar, 2019) categorizes funds by their investment style along two dimensions, investment type and stock size, visualized in figure 5.1. Each fund is assigned one of nine styles, based on the fund's placements along the two dimensions. The equity investment type is the horizontal category in figure 5.1, and is divided into three groups; growth, value, and blend. Morningstar uses a scoring system based on forward-looking and historical financial ratios to determine which of the three groups a stock is placed in. Further, the assigned investment type of a fund is defined by the weighting of growth-stocks to value-stocks in its portfolio. The vertical category in figure 5.1, stock size, is defined by three groups; small, mid, and large. Size groups are assigned to stocks based on their relative size in terms of market capitalization. The assigned investment-size of a fund is determined by the weighting of stock sizes within its portfolio. The fund's assigned category within both the equity type and size dimension determines its style, which places the fund within one of the boxes in figure 5.1.

**Figure 5.1:** Morningstar Style-Box

The Morningstar Style-Box categorizes funds by their investment style. The categories can be visualized as a grid consisting of nine squares, where each square represents a different investment style. The columns of the grid represent the investment type, while rows represent stock size. A fund within the black box in the middle of the grid, holds Blend and Mid stocks.




When using the style-box to compare funds across attributes, instead of comparing across nine styles, which combines the two dimensions from figure 5.1, we analyze the type- and size-dimensions separately.

**Fund Size**

We assign each fund a fund-size category based on its relative size measured by total net assets (TNA) within the sample. This grouping allows for a turnover-performance analysis, conditional on fund size. The TNA of funds are acquired from the Morningstar Direct database and are defined by Morningstar as the funds' assets net of liabilities. We create terciles based on the relative sizes of the funds in the sample, with each fund assigned to one of three groups, small, medium, or large.

**Investment Area**

Investment area is assigned by Morningstar based on which markets the funds have positions. By grouping funds based on where they are investing, we can identify any regional differences in performance, and whether turnover and skill levels vary, conditional on area of investment.

### 5.2.1 Attributes of Skill

We find large variation in values between fund categories in table 5.2, and test to what degree the cross-sectional values can be used to predict skill in the time-series.

**Table 5.2:** Cross-Sectional Values by Fund Category

Table 5.2 shows performance and Turnover by fund category as specified by the Morningstar Stylebox and Fund Size. The first two columns specify the groups for each panel, and the number of funds within groups. For all panels, we calculate the mean, standard deviation, and autocorrelation of turnover. The autocorrelation of turnover is calculated as the correlation of turnover for fund $i$ at time $t$ with turnover for fund $i$ at time $t-1$. For monthly Mean Return we calculate both gross and benchmark-adjusted, with values in %. Panel A shows the values for all funds in the sample. Panel B shows funds grouped by Stock Size Category. The Small-Large show the difference in means with corresponding t-statistics. Panel C shows funds grouped on Equity Style Investment. The Growth-Value is the difference in means with corresponding t-statistics. Panel D shows funds grouped on Fund Size, assigned by dividing the funds based on their TNA into terciles. The Small-Large is the difference in means with corresponding t-statistics. All t-statistics are enclosed by ().

| Funds | Number | Fund Turnover | | | Mean Return | |
|---|---|---|---|---|---|---|
| Included | of funds | Mean | St.dev. | Autocorrelation | Gross | Excess |
| Panel A: Full Sample | | | | | | |
| All | 216 | 0.640 | 0.712 | 0.328 | 0.968 | 0.135 |
| Panel B: Stock Size Categories | | | | | | |
| Small-Cap | 10 | 0.738 | 0.937 | 0.604 | 1.081 | 0.178 |
| Mid-Cap | 91 | 0.628 | 0.738 | 0.313 | 1.036 | 0.169 |
| Large-Cap | 110 | 0.635 | 0.653 | 0.239 | 0.903 | 0.102 |
| Small - Large | | 0.103 | 0.284 | 0.365 | 0.178 | 0.076 |
| (t-stat) | | (3.84) | (2.48) | (1.45) | (1.19) | (1.04) |
| Panel C: Equity Style Investment | | | | | | |
| Growth | 54 | 0.729 | 0.731 | 0.277 | 1.004 | 0.178 |
| Blend | 95 | 0.619 | 0.648 | 0.328 | 0.913 | 0.065 |
| Value | 62 | 0.587 | 0.765 | 0.382 | 1.021 | 0.225 |
| Growth - Value | | 0.142 | -0.034 | -0.105 | -0.017 | -0.093 |
| (t-stat) | | (10.39) | (-1.04) | (-0.14) | (-0.20) | (-2.49) |
| Panel D: Fund Size | | | | | | |
| Small | 70 | 0.729 | 0.794 | 0.180 | 0.707 | 0.002 |
| Medium | 70 | 0.759 | 0.815 | 0.411 | 0.984 | 0.156 |
| Large | 70 | 0.495 | 0.518 | 0.315 | 1.115 | 0.199 |
| Small - Large | | 0.228 | 0.276 | -0.135 | -0.408 | -0.197 |
| (t-stat) | | (18.33) | (4.27) | (-0.58) | (-4.95) | (-5.74) |

Recall equation 3.15 that formalizes the relationship between the time-series and cross-sectional coefficients, which we use to infer skill from the cross-sectional findings in table 5.2:

$$b - h = c(1 - \rho) \tag{3.15}$$

Where $b$ and $h$ are the slopes of the turnover-performance relationship in the time-series and cross-section, respectively, $c$ is the cost level, and $\rho$ is the autocorrelation (persistence) in turnover.

In Panel A for the full sample, we observe that average turnover in the sample period is 64%, which is 33% lower than Ľuboš Pástor and Taylor (2017) observe in their study (85%). From equation 3.4 in section 3.1, optimal turnover in response to profit opportunities is reduced from an increase in trading costs ($c$), which we find in 5.1 using equation 3.15 to be around 21% higher for the Norwegian compared to the U.S. funds[17]. As our study uses a different sample period[18], there might be other factors influencing the observed difference in average turnover, however, a large portion can be explained by the implied difference in cost ($c$) between the two fund groups.

In panel B, grouping funds by stock size category, we find that funds investing in large stocks underperform on average, relative to funds holding small and medium sized stocks, with excess return increasing with a decrease in stock size. There is a significant difference in the average level of turnover, where turnover is increasing as stock size decreases. Ľuboš Pástor and Taylor (2017) argue that small-cap stocks are generally less liquid than large-cap stocks, which in equation 3.15 leads to a higher cost ($c$) for the small-stock fund group. The small category also displays the highest persistence ($\rho$) in turnover, which for the time-series coefficient ($b$) in equation 3.9, will make a funds profit from the previous periods turnover more likely to be offset by the cost from turnover this period. According to equation 3.15, the combination of an increased c and a higher $\rho$, will affect the coefficient in the turnover-performance time-series relation in opposite directions. The autocorrelation in the small-cap category is substantially higher than for large and mid, meaning that unless the small-cap group incurs double[19] the cost level of mid and large,

[17] 2.1% versus 1.75%.

[18] Time period 2000-2022 versus 1979-2011.

[19] Using $\rho$ for the two groups from Panel B in table 5.2 and solve for the difference $c$ that makes the two slopes identical in 3.15.

the model predicts that the small-cap group will perform comparatively worse in the-time series relation.

Grouping funds by equity style investment in panel C, we find that funds in the blend category underperform compared to growth and value, with value funds being top performers. Average level of turnover increases as one moves from value to growth, with the difference in means being highly significant for both excess return and turnover. Blend is performing dramatically worse than the two other categories, with its excess return being less than about one third of the growth category, which is the second-best performer. Berk and Green (2004) find that the costs ($c$) for funds investing in value and growth are similar, measured in units of turnover. Although blend funds are the worst performing group in terms of excess returns, equation 3.15 predicts, based on similar cost levels ($c$) across investment styles that the value category having the highest persistence $\rho$, will show the least skill in the time-series.

Panel D shows an inherent fund size effect in our sample. Return increases with fund size, both before and after adjusting for benchmark returns, and turnover increases with a decrease in size. Yan (2008) finds a non-linear relationship between fund size and performance, where performance initially increases with size before decreasing. In our sample, all but four funds place within the groups found by Yan (2008) to have increasing effect on performance from an increase in net assets, which is consistent with our benchmark-adjusted returns in panel D. Adams et al. (2022) find an inverse relationship between fund size and trading cost ($c$). Autocorrelation of turnover is increasing in fund size[20], meaning that for small funds, the profits from the previous periods' turnover are comparatively less likely to be offset by the costs of turnover in the current period. From equation 3.15, the combination of a higher $c$ and lower $\rho$ in small funds, predicts a stronger turnover-performance relationship for small funds in the time-series.

[20]Although Medium display the highest autocorrelation.

**Table 5.3:** Turnover-Performance by Fund Category

Table 5.3 shows the regression outputs of the Turnover-Performance relationship grouped by the Morningstar Stylebox and Fund Size. For all four panels the dependent variable is the Benchmark-Adjusted Return. The regression specification is the same for all panels with Fund-Fixed Effects. The standard errors are robust, clustered by time and Morningstar Category Index. Panel A shows the regression outputs for funds grouped by Stock Size Category. Panel B shows the regression outputs for funds grouped by Stock Type Category. Panel C shows the regression outputs for funds grouped by their Fund Size Category. For all panels the t-statistics are enclosed by () below coefficients.

| | *Dependent variable: Benchmark-Adjusted Return* | | | |
|---|---|---|---|---|
| | **Panel A: Stock Size Categories** | | | |
| | Small Cap | Mid Cap | Large Cap | Small-Large |
| $Turnover_{t-1}$ | -0.00076*** | 0.00281*** | 0.00203* | -0.00279** |
| *(t-stat)* | (-5.60) | (4.41) | (1.95) | (-2.67) |
| | **Panel B: Stock Type Categories** | | | |
| | Growth | Blend | Value | Growth-Value |
| $Turnover_{t-1}$ | 0.00222* | 0.00130* | 0.00222** | 0.00000 |
| *(t-stat)* | (1.84) | (1.94) | (2.21) | (0.00) |
| | **Panel C: Fund Size Categories** | | | |
| | Small | Medium | Large | Small-Large |
| $Turnover_{t-1}$ | 0.00243*** | 0.00148** | 0.00197 | 0.00046 |
| *(t-stat)* | (2.99) | (2.46) | (1.52) | (0.30) |
| *Note:* | | | *p<0.1; **p<0.05; ***p<0.01 | |

Next, we examine the relationship between turnover and performance, conditional on the classification of funds in the Morningstar Stylebox and their respective size categories. For all regression outputs in panel A-C, we use the regression model 4.1, with a fund-fixed effects specification. Standard errors are clustered on both time and Morningstar Category Index in all panels.

The results in panel A suggest, given equation 3.9, that the high autocorrelation ($\rho$) of small-cap funds is proportionally larger than their increased costs ($c$). We observe a negative relationship for small-cap funds, indicating that fund managers within this category lose money from increasing trading.

In table 5.3 panel B, grouping funds on stock-type category, Blend displays the weakest relationship which contradicts with the prediction from section 5.2. With identical coefficients, the level of skill displayed by Growth and Value are identical, with value having the statistically stronger relationship. The results suggest that fund managers specializing in one investment style, as opposed to having a mixed stock holding of both value and growth in their portfolios, display higher levels of skill.

In panel C grouping funds by size, the skill level falls as fund size increases, as predicted from the cross-section. Smaller funds display the highest skill and statistical significance. The slope is steeper for large funds than medium, however, only medium holds a relationship of statistical significance. Pollet and Wilson (2008) find that as funds grow in size they experience diminishing returns to scale, and that their investment strategies do not scale well with the increase in size, which could explain the effect we observe. The small funds display the highest skill level, which Ľuboš Pástor and Taylor (2017) argue could be caused by small funds trading smaller amounts, enabling them to better exploit mispricing opportunities without causing a market impact.

The relationship between the cross-sectional ($h$) and the time-series ($b$) slope works relatively well in predicting performance. As a model is a simplified version of reality, and the funds within groups exhibit high variation in parameter values, a wrong estimation does not necessarily make the relationship break. Additionally, there are a lot of factors potentially influencing the relationship, that the simplified model in 3.15 does not consider.

### 5.2.2 Skill by Investment Strategy

Next, we examine the turnover-performance relationship conditional on the investment area of funds. We group funds into two categories, funds that only invest in one country (Single-Area funds), and those investing in multiple (Multi-Area funds). We do this to examine whether level of skill differs in market specialization, and if a single-area strategy enables fund managers to have better knowledge in that area, which in turn would enable them to identify and exploit mispricing opportunities in that area better. Conversely, the access to more mispricing opportunities for fund managers, might enable the multi-area funds to have a higher skill coefficient in the turnover-performance relation. Lastly, we test for horizon-effects in the turnover-performance relationship and offer potential explanations to the observed effects. This section of the analysis is novel and has not been done by Ľuboš Pástor and Taylor (2017) and serves as an extension in examining skill conditional on investment area.

Recall regression equation 4.1 that shows how return in period $t$, is caused by profit from trades in the previous period $(t-1)$, minus the cost from exploiting profit opportunities this period $(t)$. If funds with different market exposure[21], as a consequence exhibit a significant difference in investment strategy, it could cause the length of $(t)$ in regression equation 4.1 to differ, altering the relationship between turnover and performance dependent on the definition of $t$. We define horizon-effects, as profit realizations that happen prior to, or after the main payoff from exploitation of profit opportunities, which according to 4.1 is in $(t+1)$ where the defined length of $t$ equals 1 year.

**Table 5.4:** Turnover-Performance by Investment Area

Table 5.4 shows the regression output of the Turnover-Performance relationship with funds grouped by Investment Area single and multi. The dependent variable is the Benchmark-Adjusted Return, using a fund-fixed effects specification. The independent variables are turnover with one time-lag $(t-1)$ in the first row, and the turnover without time-lag $(t)$ in the second. Standard errors are robust, clustered by Time and Morningstar Category Index (MCI). T-statistics are reported below coefficients, enclosed by ().

| | *Dependent Variable:* *Benchmark-Adjusted Return* | |
|---|---|---|
| Invesment Area: | Single-Area | Multi-Area |
| $Turnover_{t-1}$ | 0.00085*** | 0.00247*** |
| (t-statistic) | (4.69) | (2.54) |
| $Turnover_t$ | 0.00111*** | 0.00115 |
| (t-statistic) | (4.88) | (1.11) |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 | |

In table 5.4, with independent variable turnover$_{t-1}$ $(X_{t-1})$, the multi-area investment fund group display the highest level of skill with a coefficient of 0.00247, a result that is also highly significant (t= 2.54), with a stronger slope than the full sample slope in table 5.1 of 0.00182 for the same specifications. For single area funds the relationship is weaker (0.00085), with only about half the coefficient found in table 5.1 (0.00182), suggesting that funds specializing in a single market display less skill, compared to multi-area funds. It is reasonable based on the dynamics of profit opportunities discussed in section 3.1, specifically that given that mispricing opportunities are time-varying in nature, the access to a broader market gives skilled managers access to a higher number of mispricing opportunities, compared to funds investing in single market only. The single-area funds

[21] i.e., Market exposure from different countries.

therefore have higher constraints than multi-area do, as they are limited to their area in exploiting mispricing.

The weakened coefficient (slope) observed for single-area funds with turnover$_{t-1}$, could to some extent be a consequence of a difference in investment strategy for the two groups, in turn creating horizon effects. Replacing $\mathrm{X}_{t-1}$ with $\mathrm{X}_t$ and $\mathrm{X}_{t-2}$ in our regression equation (4.1), we observe how it affects the results. With the independent variable set to $X_t$ we find an altered skill relationship compared to $X_{t-1}$, where the single-area displays a stronger relationship with a coefficient of 0.00111, which is also highly significant (t-stat=4.88). The multi-area maintains a positive relationship (coefficient) with $X_t$, although it is no longer statistically significant. This is one of the main findings in our empirical results and is an interesting finding of how the identification of skill is dependent on horizon-effects for funds with differing investment scope. The results show that single-area funds have the main portion of profit realizations happening in the same period as the trade, whereas multi-area have a profit realization in the year after the trade is executed. For $X_{t-2}$, neither area display a relationship of significance.

We show the distribution of fund characteristics for the two investment-areas within the Morningstar style box described in section 5.2, and discuss why we observe the characteristics in the single- and multi-area fund groups.

**Table 5.5:** Stock Attributes for Funds Grouped by Investment Area

Table 5.5 shows the distribution of funds within categories for funds with a single-area investment strategy in Panel A, and a multi-area investment strategy in Panel B. Stock-Size, Stock-Type and Fund-Size are fund categories, while $n$ denotes the number of funds within each category.

Panel A: Single-Area

| Stock Size | n | Stock Type | n | Fund Size | n |
|---|---|---|---|---|---|
| Small-cap | 8 | Growth | 10 | Small | 19 |
| Mid-cap | 59 | Blend | 30 | Medium | 25 |
| Large-cap | 7 | Value | 34 | Large | 27 |

Panel B: Multi-Area

| Stock Size | n | Stock Type | n | Fund Size | n |
|---|---|---|---|---|---|
| Small-cap | 2 | Growth | 41 | Small | 50 |
| Mid-cap | 31 | Blend | 62 | Medium | 42 |
| Large-cap | 96 | Value | 26 | Large | 39 |

The most salient difference between multi- and single-area is the size of their stock holdings, with multi-area mainly holding large-cap stocks, whereas single-area mainly are investing in mid-cap stocks. The lesser constraints in terms of investment possibilities facing multi-area funds, comes at the cost of increased information complexity. A possible explanation as to why multi-area funds mainly hold large-cap stocks, might be that as access to information increases, so does complexity in processing it. Fund managers as a result, turn to stocks that are highly covered by analysts, to mitigate some of the increased complexity. Conversely, the single-market constraint reduces information complexity, which could enable a deeper market knowledge among fund managers, leading them to exploit mispricing in less covered stocks[22]. This might also explain the difference seen in Stock Type category, where multi-area funds are more diversified in their stock holdings than the single-area funds, with the highest number of multi-area funds placing within the style category Blend, whereas single-area have most funds in Value. By having a more diversified portfolio, multi-area funds might rely more on a diversified approach to mitigate the complexities of analyzing numerous markets, with varying degrees of information availability.

We emphasize that the dynamics regarding the horizon effects are complex, and most likely highly conditional on the individual fund's investment strategy and characteristics, however, we offer some general possible explanations for the horizon effects observed in table 5.4. For funds in single- and multi-area, the kind of mispricing they capture could differ. For single-area funds, a deeper market familiarity and specialization to their market's dynamics may enable quicker decision-making when identifying profit opportunities. Furthermore, single-area funds are not subject to many of the factors that might hinder multi-area funds to capitalize on short-horizon profit opportunities. If a fund invests in multiple markets, it faces an increase in complexity regarding currency risk, which could hinder its agility to make trades that capitalize faster. Massa et al. (2011) find that less diversified global funds face an increase in currency risk, that may be mitigated by an increase in diversification, often at the expense of performance. Additionally, multi-area funds must comply with the regulatory framework of all markets they operate in, whereas single-area funds have a more straightforward regulatory landscape to navigate. The relationship being strongest with $X_{t-1}$ for multi-area funds, could be caused by the funds

[22] Coval and Moskowitz (1999) finds results in line with this assertion.

in this group being able to capitalize on macroeconomic trends that might not be present in a single-market, which take more time before being priced in the individual securities. Single-area funds displaying short horizon effects, may come from the funds capturing mispricing that is more short-lived in nature and comes from smaller, less researched stocks, and a higher degree of stock selection, as found by Coval and Moskowitz (1999), with consequently shorter realization time[23].

[23]Although the relationship is not straightforward.

# 6 What explains Turnover?

We find in section 5 that fund managers display skill in exploiting profit opportunities, we identify in 5.2.1 and 5.2.2 how skill varies based on a fund's investment style, size, and area. In this section we examine what explains turnover. We use Liquidity, Sentiment, Distress Risk, and Volatility as proxies for market mispricing to explain turnover. In the first part, we describe how the variables are constructed for each investment area, then which method is used to identify the relationship, before analyzing the results in 6.3 and 6.4. We analyze turnover for the two largest investment areas, Global and Norway, which represent the investment groups multi- and single-area respectively.

We separate on investment area because we expect to see differences in driving dynamics of turnover between the multi and single area funds. As found in 5.2, the average turnover level, persistence in turnover and skill displayed in table 5.4, differs based on whether a fund is investing in a single or in multiple markets. The difference in trading behavior of fund managers between the two groups might display heterogeneity in which proxies for mispricing drive turnover.

## 6.1 Variable Construction

The explanatory variables are chosen based on being potential proxies for mispricing in equity markets. We use liquidity, PE-ratio, PB-ratio, and volatility, which have all been shown in previous studies to have associations with periods that could be prone to mispricing.

**Liquidity**

*(Price Efficiency)*

Liquidity is included due to the effect it has on price efficiency and transaction costs. Liquid markets are more efficient, reducing transaction costs with more information being reflected in prices (Zeng & Jin, 2023). The relationship between turnover and liquidity is entirely dependent on which of the effects are stronger, i.e., low liquidity promotes an increase in turnover due to a potential rise in mispricing opportunities, while an increase in transaction costs could drive a corresponding reduction in turnover. The gain from mispricing in relation to the accompanied rise in transaction costs, will determine liquidity's effect on trading.

We use the Amihud illiquidity estimator (Amihud, 2002) to measure market illiquidity. Separate illiquidity estimates are computed for investment area Norway and Global using individual securities listed on the OSEAX and MSCI world index, which are then aggregated for each index, to get the market illiquidity.

$$ILLIQ_y = 10^6 \left( \frac{1}{D_{iy}} \sum_d \frac{|R_{iyd}|}{VOLD_{iyd}} \right) \tag{6.1}$$

Where $R_{iyd}$ are daily returns for stock $i$ in week $y$ at day $d$, and $VOLD_{iyd}$ being daily trade volume scaled by the stock price. Prices and volumes are retrieved from Morningstar Direct, which are used to calculate the illiquidity per week, with the weekly illiquidity estimates then averaged on a per-month basis. For interpretation purposes, we negate the Amihud illiquidity estimator, making it a measure of liquidity.

**Price-Earnings Ratio**

*(Investor Sentiment)*

The PE ratio is a measure comparing current earnings to expected future earnings. Rahman and Shamsuddin (2019) find that increases in investor sentiment typically are accompanied by a rise in the PE ratio. Further, Stambaugh et al. (2012) find that mispricing occurs in periods where sentiment changes rapidly, with the effect stronger for periods characterized by high sentiment, rather than low. With a market-wide increase in sentiment, skilled managers might identify the associated mispricing and trade to capture these, increasing turnover. Hence, we expect to see a relationship between the sentiment and fund turnover, based on shifts in sentiment, with Stambaugh et al. (2012) arguing that the high sentiment periods will attract sentiment-driven investors, making the fund managers trading on this mispricing, more likely to do so when sentiment is high.

General PE-ratio:

$$PE - Ratio_i = \frac{Price\ per\ Share_i}{Earnings\ per\ Share_i\ (EPS)} \tag{6.2}$$

We use the PE ratio from the OSEAX and MSCI world index as provided by Bloomberg. This calculation is initially performed at the individual stock level and then aggregated to the index level. The ratio is on a monthly basis.

**Price-Book Ratio**

*(Distress Risk)*

The price-book (PB) ratio is a measure of the market value of a firm's equity relative to the book value. Fama and French (1995) and Chen and Zhang (1998) find that firms with a low PB-ratio display persistently lower earnings, higher leverage and uncertainty related to earnings compared to high-PB firms. Griffin and Lemmon (2002) expand on these findings, showing that low-PB firms have an elevated distress risk, with the effect most pronounced for smaller firms. A market-wide increase in distress risk, could lead to an increase in uncertainty regarding market prices, which skilled managers might exploit.

General PB-ratio:

$$PB - Ratio_i = \frac{Price\ per\ Share_i}{Book - Value\ per\ Share_i} \tag{6.3}$$

PB values for the Norwegian and global investment area are the monthly aggregate PB values from the OSEAX and MSCI global indices respectively as provided by Bloomberg.

**Volatility**

*(Uncertainty and Risk Management)*

Volatility is a measure that gauges the dispersion in market prices over a given period of time. Periods with high volatility can be characterized as of higher risk, and more uncertainty in prices. Further, periods of increased volatility have been found to cause herding, a phenomenon where market participants ignore fundamentals and instead align with the market's movement (Yang & Chuang, 2023). Herding behavior is shown to cause market prices to deviate from their fundamental values (Nofsinger & Sias, 1999). A deviation from an assets fundamental value would lead to profit opportunities, that skilled fund managers might capitalize on, driving turnover. High volatility can also be due to fundamental changes in the market environment, leading prices to adjust based on updated information regarding the market outlook, which in turn cause funds to reassess their portfolios, further driving turnover.

From a risk-management perspective, increased volatility might also drive turnover. In e.g., Value at Risk (VaR), which quantifies the maximum potential loss in the value of a portfolio over a set period for a given confidence level, under normal market conditions, is sensitive to changes in volatility. If volatility increases, so does potential losses. This dynamic could drive fund managers to trade more, to reduce their potential loss exposure, as markets become more volatile.

For funds within the global investment area, we use the CBOE volatility index (VIX). It estimates the implied volatility using put and call prices of securities from the S&P 500 Index. Although estimation is performed exclusively with U.S. equity as the underlying, we assume that the VIX estimate is a good proxy for global volatility, because of the interconnectivity of the US market with the global economy (Reserve, 2018). We use the average monthly levels of the VIX index.

The VIX index does not accurately reflect the volatility of the Norwegian market, as the Norwegian economy is less diversified in assets, resulting in a lower correlation with the global volatility[24] (Anfinsen & Johansen, 2017). For volatility, we use the standard deviation of the OSEAX index, which contains all stocks on the Oslo Stock Exchange. Monthly standard deviation is computed from daily OSEAX returns, which are retrieved from Bloomberg.

**Market Return**

*(Control for Market Movement)*

We include the market return as a control variable for trading activity caused by stock market returns during the sample period. The indices we use for the Norwegian and Global market are the OSEAX and MSCI world with return being gross returns as defined in section 2.1, with data retrieved from Bloomberg.

**Time Trend**

*(Control for Inflation and/or Tech. Development)*

We use time trend to control for certain unobservable factors that may impact turnover over time. Time trend is used in financial studies as a control for inflation and development

[24]As measured by VIX.

in technology[25]. The variable is constructed as an integer that counts the number of months since the first month of observations over the entirety of the sample period.

## 6.2 Regression Models

**Specifications**

We run two multivariate regression models for both investment area Global and Norway, with the four mispricing proxies as independent variables. In the first model the dependent variable is turnover, applying a specification of fund-fixed effects. With this specification, the estimated coefficients are controlled for heterogeneity in turnover between funds that arises from of e.g., differences in investment strategy[26]. The second model is a pooled regression with the dependent variable being average turnover, where turnover is averaged across funds within each investment area. This provides insights into what explains turnover for the entire group and smooths out idiosyncratic fund characteristics that might not represent overall market drivers, which might be more prevalent in the model with fund-fixed effects.

**Error Terms**

For the regression model with fund turnover as dependent variable and fund-fixed effects, we make the standard errors robust by clustering on Morningstar Category Index (MCI) and time, because of observed correlation of error terms within the MCI as discussed in 4.3. When averaging turnover across the two investment area groups, the error terms in our regressions exhibit autocorrelation as a result of the funds on an individual level having persistence in turnover as found in 5.2.1. To address this autocorrelation, we apply the Newey-west estimator in treatment of error terms with 24-month lag (2 year), to make our standard error estimation more consistent, improving the reliability and reducing heteroskedasticity (Newey & West, 1987).

**Collinearity Between Explanatory Variables**

We use the four mispricing factors described in 6.1, in the two regression models to explain drivers of turnover. From visual inspection we suspect a linear relationship between the

[25] Or other trends that are expected to grow linearly over time.
[26] See section 4.2.1.

four mispricing proxies. Concerns of multicollinearity among explanatory variables in a regression model can significantly influence the results, leading to unreliable and unstable estimates of regression coefficients. Multicollinearity occurs when independent variables are highly correlated, making it difficult to isolate the individual effect of each variable. This can result in exaggerated standard errors, reduced statistical power, and coefficients that may not accurately reflect the true relationship with the dependent variable. To address the concerns of multicollinearity of our independent variables in both models, we perform a VIF tests[27], that show levels below what is regarded as considerable[28].

## 6.3 Global Drivers of Turnover

We run two regression models for investment area Global. In the first model the dependent variable is turnover, with the specifications fund-fixed effects. The second model is a pooled regression with dependent variable average turnover. We run the four mispricing factors described in 6.1, in both models.

[27]See appendix C.

[28]Johnston et al. (2018) argue that a VIF-value above 2.5 is considerable.

**Figure 6.1:** Investment Area Global: Average Turnover and Mispricing Proxies

The figure illustrates the development of average turnover and mispricing proxies for funds with a global investment area. Figure A shows the average annual turnover between 2000 and 2022. Figure B shows the monthly development of four mispricing proxies: Liquidity, Volatility, Distress Risk and Sentiment between 2000 and 2022. $\tau$ denotes the correlation with average turnover for each mispricing proxy.

Figure A: Global Average Turnover 2000-2022

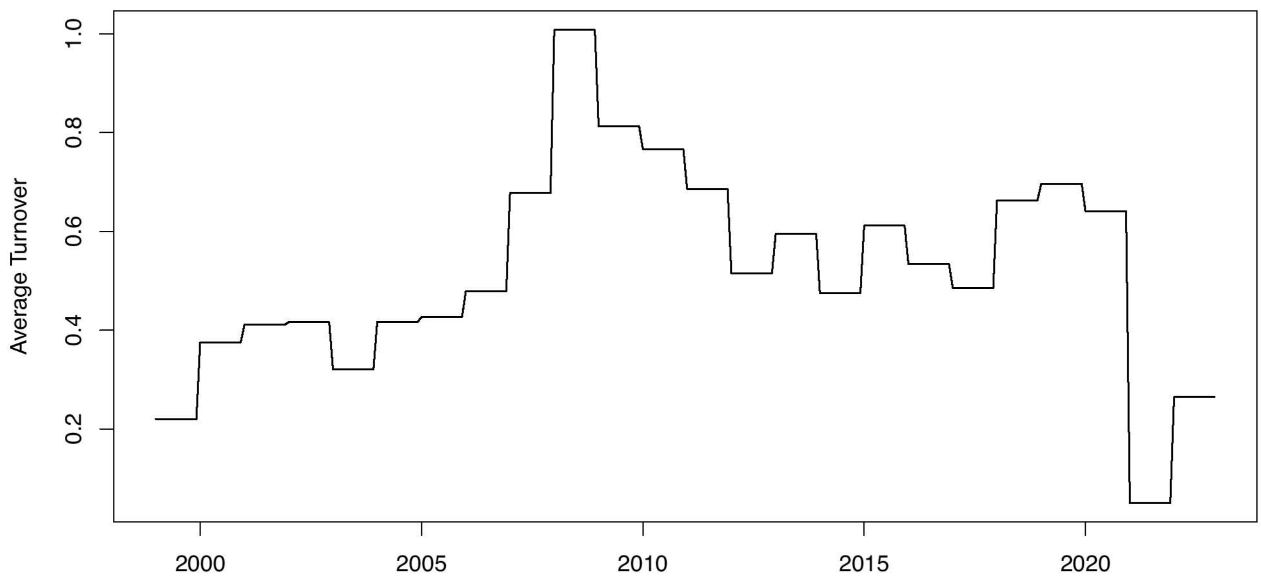



Figure B: Global Mispricing Proxies 2000-2022

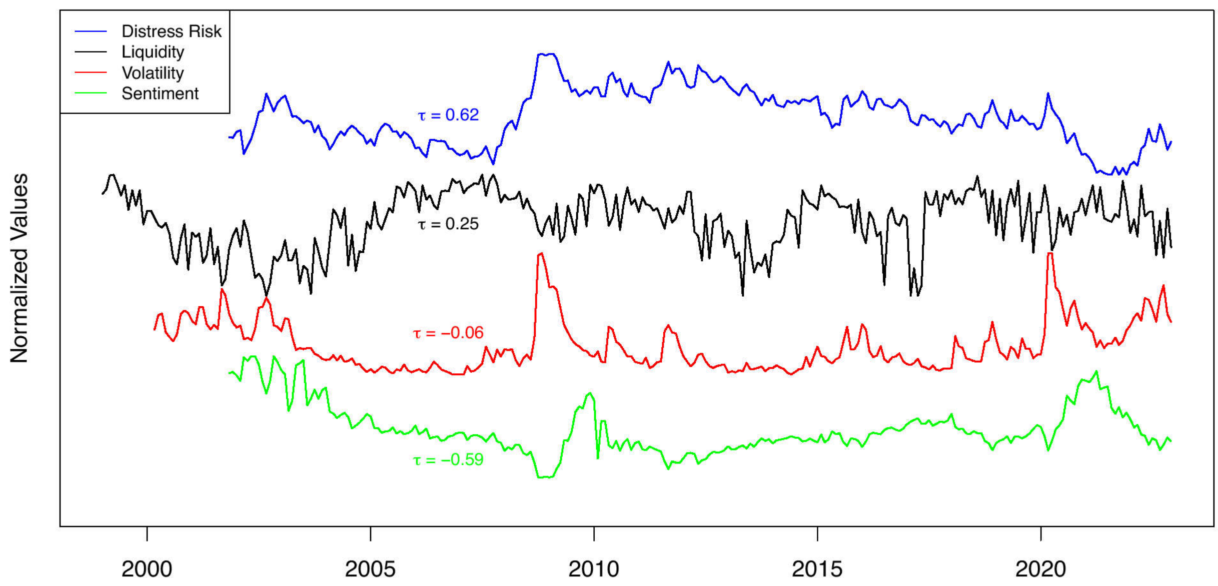


**Table 6.1:** Turnover Regressions for the Global Investment Area

Table 6.1 shows regression outputs for funds with a global investment area. For regressions (1)-(5), the dependent variable is turnover, with specifications Fund-fixed effects, and robust standard errors clustered on both time and Morningstar Category Index. For regressions (6)-(10), the dependent variable is Average Turnover for all funds in investment area Global, and standard errors are robust using the Newey-West estimator with 24 months of lag. For all models (1)-(10) the independent variables are liquidity, sentiment, distress risk, volatility, market return and time trend. T-statistics are reported below all coefficients, enclosed by ().

| | *Dependent variable:* | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | $Turnover_{i,t}$ | | | | | $Average\ Turnover_t$ | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| $Liquidity_t$ | 1.955** | | | | 2.618*** | 2.487 | | | | 4.407*** |
| | (2.52) | | | | (3.02) | (1.44) | | | | (3.92) |
| $Sentiment_t$ | | −0.850* | | | −0.411 | | −2.970*** | | | −1.373** |
| | | (−1.77) | | | (−0.82) | | (−5.17) | | | (−2.10) |
| $Distress\ Risk_t$ | | | 6.494 | | 4.260 | | | 30.503*** | | 25.725*** |
| | | | (1.14) | | (0.60) | | | (3.29) | | (2.63) |
| $Volatility_t$ | | | | 0.049** | 0.051* | | | | −0.012 | 0.023 |
| | | | | (2.16) | (1.82) | | | | (−0.26) | (0.95) |
| $Market\ Return_t$ | | | | | 0.866 | | | | | 5.738 |
| | | | | | (0.37) | | | | | (1.01) |
| $Time\ Trend_t$ | −0.298*** | −0.307*** | −0.304*** | −0.316*** | −0.311*** | 0.020 | −0.068 | −0.019 | −0.002 | −0.056 |
| | (−4.64) | (−4.82) | (−4.69) | (−4.78) | (−4.72) | (0.31) | (−1.16) | (−0.323) | (−0.04) | (−1.32) |
| Observations | 8,952 | 8,844 | 8,844 | 8,924 | 8,844 | 288 | 254 | 254 | 274 | 254 |
| *Note:* | | | | | | | | | | *p<0.1; **p<0.05; ***p<0.01 |

Of our four proxies for mispricing, only liquidity and volatility hold explanatory power looking at individual drivers of turnover controlling for fund-fixed effects, while for average turnover, liquidity, sentiment, and distress risk hold explanatory power.

Liquidity holds the highest explanatory power of turnover in both models. The slope is positive, suggesting that the mispricing that might occur from low liquidity, is not captured by fund managers, and that they instead increase trading as liquidity increases. The relationship is pronounced on aggregate in (10), meaning that on group level, an increase in liquidity leads to a general increase in turnover-level for funds investing in the global market. In figure B in 6.1, the liquidity has a correlation ($\tau$) to average turnover of 0.25. Furthermore, as we argue in 5.2.2 the multi-area funds turn to larger stocks for information simplicity, with large-cap stocks being inherently high in liquidity, the observed relationship between liquidity and turnover is interesting, and could be a consequence of the lower cost from an increase in liquidity making the investment strategies cheaper to implement for fund managers. The increased liquidity also allows for easier entry and exit of active positions, reducing any liquidity risks of holdings, which if holding multiple positions in multiple markets could be a concern.

Investor sentiment is not a strong driver of turnover on fund-level (5), but on aggregate in (10) the slope is negative, and of statistical significance. A negative slope implies a general reduction in trading activity as investor sentiment increases, but this does not seem to drive fund-managers on an individual basis. The correlation between average turnover and sentiment is highly negative[29] ($\tau = -0.59$), the association, could e.g. be a consequence of fund managers having anticipated a coming increase in sentiment, holding onto their positions instead of realizing them. Sentiment does, however, seem to increase in the aftermath of recessions, where a funds disposable capital might be limited. The lack of significance with fund fixed effects indicates that sentiment as a mispricing proxy, is not a primary driver of turnover among fund managers.

Distress risk holds a positive relationship to turnover, with the relationship only significant with average turnover as dependent variable (10). The results suggest that on average funds increase turnover with distress risk, but that it is not a primary driver. Distress risk has the strongest correlation with average turnover ($\tau = 0.62$), and a high coefficient (25.725), which shows that shifting market risk is highly associated with level of turnover, and that for multi-area funds the relationship is positive.

In (5), an increase in volatility is associated with increased trading activity, however, it does not hold explanatory power in the aggregate in (10). The relationship is weak statistically in (5), and a weak slope suggest a positive but small increase in trading activity from an increase in volatility, which could be caused by periods of higher volatility making risk management concerns more important, or that the periods of higher volatility have higher mispricing, captured by multi-area funds. From figure 6.1, it is apparent that the average level of turnover is affected in both directions from a significant increase in volatility. In the period leading up to the financial crisis of 2008 turnover increases with volatility, while in 2020 the effect from volatility on turnover is inverse.

## 6.4 Norwegian Drivers of Turnover

We perform the same analysis of what explains turnover for funds with investment area in Norway, as was done for global funds in section 6.3. The only difference in variable construction as opposed to Global, is the volatility[30] variable.

[29] Figure B in 6.1.
[30] This is specified in section 6.1.

**Figure 6.2:** Investment Area Norway: Average Turnover and Mispricing Proxies

The figure illustrates the development of average turnover and mispricing proxies for funds with a Norwegian investment area. Figure A shows the average annual turnover between 2000 and 2022. Figure B shows the monthly development of four mispricing proxies: Liquidity, Volatility, Distress Risk and Sentiment between 2000 and 2022. $\tau$ denotes the correlation with average turnover for each mispricing proxy.

Figure A: Norwegian Average Turnover 2000-2022

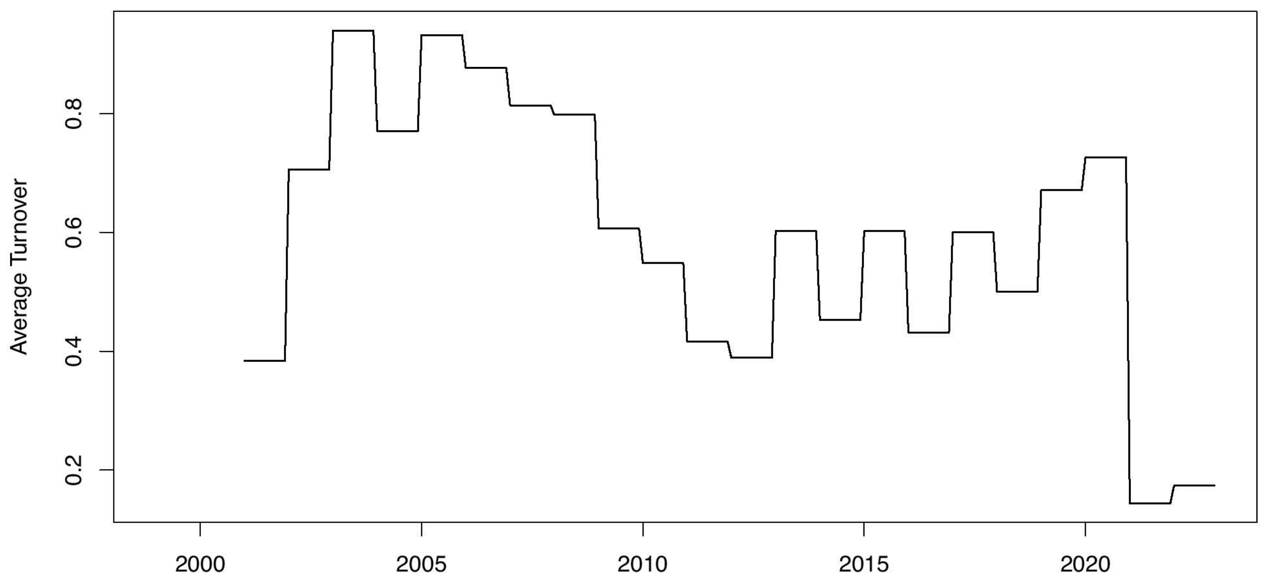



Figure B: Norwegian Mispricing Proxies 2000-2022

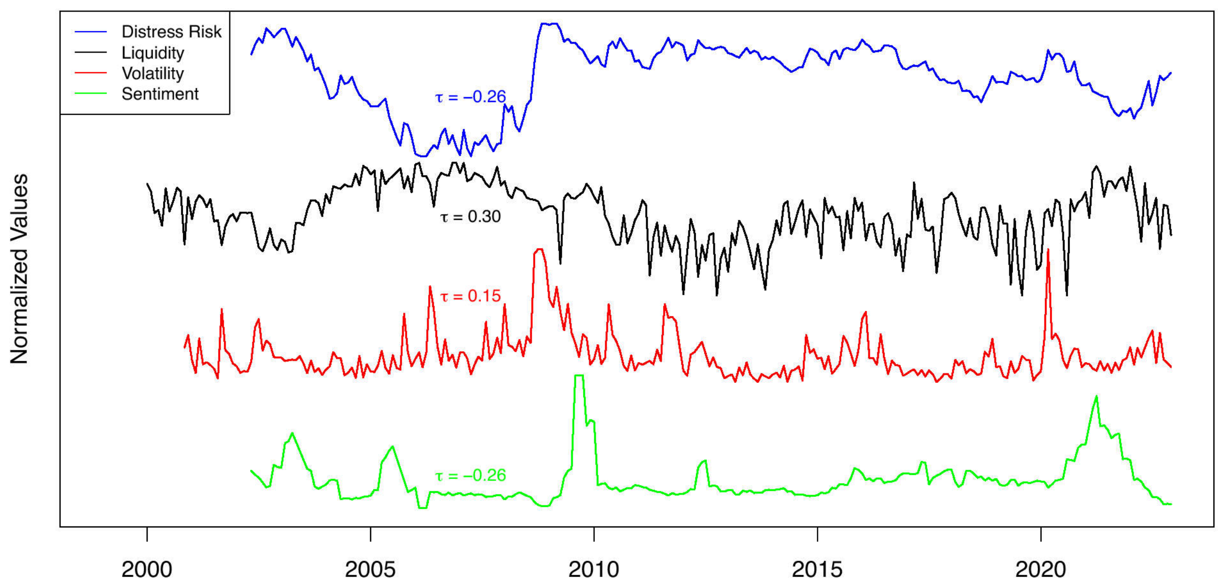


**Table 6.2:** Turnover Regressions for the Norwegian Investment Area

Table 6.2 shows regression outputs for funds with investment area Norway. For regressions (1)-(5), the dependent variable is turnover, with specifications Fund-fixed effects, and robust standard errors clustered on both time and Morningstar Category Index. For regressions (6)-(10), the dependent variable is Average Turnover for all funds in investment area Norway, and standard errors are robust using the Newey-West estimator with 24 months of lag. For all models (1)-(10) the independent variables are liquidity, sentiment, distress risk, volatility, market return and time trend. T-statistics are reported below all coefficients, enclosed by ().

| | *Dependent variable:* | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $Turnover_{i,t}$ | | | | | $Average\ Turnover_t$ | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| $Liquidity_t$ | 2.654** | | | | 0.120 | 1.545 | | | | −0.918 |
| | (2.12) | | | | (0.21) | (0.72) | | | | (−0.66) |
| $Sentiment_t$ | | −0.035 | | | 0.012 | | −0.149 | | | −0.089 |
| | | (−0.48) | | | (0.159) | | (−1.07) | | | (−0.61) |
| $Distress\ Risk_t$ | | | −14.546** | | −16.880*** | | | −9.741* | | −12.098*** |
| | | | (−2.34) | | (−2.61) | | | (−1.79) | | (−2.63) |
| $Volatility_t$ | | | | 3.741** | 6.571** | | | | 1.101 | 1.291 |
| | | | | (1.99) | (2.46) | | | | (0.45) | (0.47) |
| $Market\ Return_t$ | | | | | 1.882 | | | | | 0.168 |
| | | | | | (0.93) | | | | | (0.048) |
| $Time\ Trend_t$ | −0.260*** | −0.280*** | −0.266*** | −0.269*** | −0.241*** | −0.155** | −0.206*** | −0.211*** | −0.160** | −0.204*** |
| | (−4.45) | (−4.74) | (−4.65) | (−4.32) | (−4.23) | (−2.36) | (−4.00) | (−4.16) | (−2.49) | (−3.86) |
| Observations | 7,871 | 7,817 | 7,856 | 7,872 | 7,817 | 263 | 242 | 248 | 264 | 242 |
| *Note:* | | | | | | | | | | *p<0.1; **p<0.05; ***p<0.01 |

For funds investing in Norway, our proxies for mispricing only return distress risk and volatility as drivers of turnover on fund-level in (5). Distress risk shows the strongest statistical significance, with a negative slope, suggesting that fund managers trade less as distress risk increases. On aggregate in (10) the negative relationship persists, suggesting that the level of turnover across funds falls as distress risk increases, opposite of that found for global funds in table 6.1. This is interesting as it shows that distress risk as an explainer of turnover between the groups, are inversely related between multi- and single-area funds.

In (5), volatility is a strong driver of turnover on fund level, suggesting that managers increase their trading activity with volatility. On average in (10) the relationship loses its explanatory power, suggesting that the effect is fund-specific, and not generally an explainer of the overall fund group.

From figure B in 6.2, we observe that the mispricing factors display a much weaker correlation to average turnover in figure A, compared to the mispricing factors for investment area Global. This suggests that there might be other mispricing factors that drive turnover for funds investing in a single-area (Norway), compared to multi-area (global), which might explain some of the horizon effects conditional on area of investment found in 5.2.2.

# 7 Robustness

In the following section we test the robustness and highlight some limitations of our empirical findings. For robustness testing we perform a placebo test of the main findings, test the impact of different time-lags to look for horizon-effects identified in 5.4, test for finite sample-bias, and stricter clustering of standard errors. Lastly, we highlight potential weaknesses in our study.

## 7.1 Placebo Test

A placebo test is a robustness test used in statistical analysis to validate the causal relationship identified in the main findings. It involves creating a 'placebo' scenario, by modifying a key aspect of the data or analysis in a way that should theoretically nullify the observed effect, if the original findings are indeed valid. This helps in distinguishing genuine effects, from those arising due to confounding factors, data mining, or sampling errors. We use the same inclusion criteria as in section 2.1, with the difference being a filter from Morningstar Direct that includes only funds classified as index funds, to design our placebo group. Ľuboš Pástor and Taylor (2017) argue that index funds are a good comparative group, as they will nullify the main findings if they achieve a positive relationship in the turnover-performance relationship, since they do not exhibit any skill caused by trading. We run equation 4.1 with the same specifications as in the main result in table 5.1, with the results showing no significance and near-zero slopes[31]. This is important as it shows that our findings are indeed unique for actively managed funds, and not due to sampling error, or a methodological weakness.

## 7.2 Horizon Effects

We test the sensitivity of the regression results examining skill found in section 5.1 and section 5.2.1 by having different lags on the independent variable turnover. We test with turnover at $X_t, X_{t-2}, X_{t-3}$, and $X_{t-4}$ in equation 4.1 to see whether there are any short- or long-horizon effects as we found for the single-area fund group in table 5.4. Our motivation to do this, is to test if turnover is indeed a good predictor of subsequent

[31] See appendix D.

returns, or if the horizon effects make the modelled relationship between turnover and performance, presented in section 3.9, not an improvement in describing the payoff structure for Norwegian mutual funds over e.g., $X_t$.

Testing the impact of the results in section 5 in table 5.1 with $X_t$ as independent variable in regression 4.1, we find considerable short-horizon effects[32], which given the funds investing in single-area displaying strong short-horizon effect as found in 5.4, is not surprising. Compared to having turnover lagged ($X_{t-1}$) in equation 4.1 in table 5.1, the relationship between turnover and performance is weaker (0.00120) but maintains high statistical significance. This suggests that a considerable amount of the turnover-performance relation in our sample is captured with $X_t$, challenging the modelled relationship.

For $X_{t-2}$, $X_{t-3}$ and $X_{t-4}$ in 4.1, neither model show statistical significance, indicating that the model presented in 3, is relatively good at capturing most of the turnover-performance relation for the full sample, despite the low resolution of turnover.

Next, we run the turnover-performance regression with different time-lags for table 5.3, grouping funds by Morningstar Stylebox and fund size. With $X_t$ in equation 4.1, we get the fund attributes that characterize the funds that capture the short-horizon effects[33]. In terms of statistical relationship with $X_t$, stock size category medium, stock type growth and blend, and fund size large, have a significant and positive coefficient. Interestingly, large funds achieve significance in the turnover-performance relationship with a short horizon, after initially not showing any significance in table 5.3, additionally, the slope of growth is increased (0.0031) with a higher significance (t-statistic = 3.67). These results show that the short-horizon effects are more prominent for large funds, and funds investing in growth stocks. With $X_{t-2}, X_{t-3}$, and $X_{t-4}$, neither grouping of funds results in a relationship between turnover and performance of significance, in line with findings from table 5.1 and 5.4. This indicates that the payoff horizon mainly occurs with $X_{t-1}$, and that previous periods turnover is indeed a predictor of this periods realized return, with short-horizon effects for single-area funds, funds large in size, and funds investing mainly in growth stocks.

[32]See appendix E, table E.1.
[33]See appendix E table E.2.

## 7.3 Finite Sample Bias

A potential issue regarding our findings using the regression model in 4.1, is that the use of a lagged variable ($X_{t-1}$) induces potential finite sample bias. Finite sample bias, in the context of econometrics, refers to the distortion that arises in parameter estimates because the available sample size is not large enough to fully capture the underlying population dynamics. When using lagged variables, such as past values of a fund's turnover rate ($X_{t-1}$) to predict current returns, finite sample bias potentially occurs if the lagged variable is correlated with an omitted variable that also affects the dependent variable. For instance, if a fund's turnover rate in the past is negatively correlated with its current or future returns, a small sample might artificially inflate the apparent correlation between lagged turnover and returns. If a funds $X_t$ is negatively correlated with its $R_t$ or $R_{t+1}$, a small sample, tends to create a positive correlation between lagged turnover and return, even if the true value is zero, an effect found by Stambaugh (1999), then tied to the regression model 4.1 by Ľuboš Pástor and Taylor (2017)[34]. We use the method proposed by Ľuboš Pástor and Taylor (2017) to address this issue, which consists of adding $R_{t-1}$ and $R_{t-2}$ as independent variables in equation 4.1 to control for the potential bias. The coefficients and statistical significance compared to results in table 5.1, change[35], indicating that the bias from this effect is present, however the effect on coefficients and statistical significance is not of a magnitude that indicates that this bias is largely confounding the turnover-performance relationship observed in the main results.

## 7.4 Clustering of Standard Errors

We argue in 4.3 in favor of clustering by time and sector using the Morningstar Category Index as a sector proxy, grounded in the observation that standard errors tend to exhibit intra-sector correlation, while showing minimal across-sector correlation. This suggests that funds within the same sector experience similar movements through time, that are not present across different sectors. Therefore, clustering standard errors by sector acknowledges the non-independence of observations within the same sector, leading to more accurate standard errors and statistical inference. However, because individual

[34] See (Ľuboš Pástor & Taylor, 2017) page 1497.
[35] See appendix F.

fund characteristics and strategies may also create correlation in error terms across time, we extend our clustering approach to fund and time. This is motivated by the need to capture any serial correlation in error terms that could arise from the unique behavior of a fund. The implications of our findings remain robust to these changes in clustering, indicating that our results are not driven by the specific method of clustering, but are instead reflective of a more fundamental relationship in the data. It also suggests that while sectoral and fund-specific effects both exist, neither dominates to the extent that one obscures the effects of the other when both types of clustering are used.

## 7.5 Limitations

The main limiting factor in our study is the lack of higher resolution of fund turnover data. Since Morningstar reports turnover on an annual basis, this may limit the precision of our results. As we identify prominent horizon effects in both the results in table 5 and in 5.4 for single-area funds, a higher frequency of turnover data would enable the identification of where the main realization from trading occurs. Furthermore, in section 6, the low resolution of turnover makes the examination of potential lead/lag dynamics between turnover and the four mispricing proxies, not viable.

Our analysis does not incorporate the use of different benchmarks when estimating benchmark-adjusted returns of funds, which could offer alternative perspectives on fund performance. The process to recreate the individual funds primary prospectus benchmarks, was highly manual, and only successful in some cases. Due this limitation, it was not possible to test whether Norwegian fund managers exhibit the same tendency identified by Sensoy (2009), in which managers choose benchmarks that are easier to beat. Testing alternative benchmarks may provide a more nuanced understanding of the dynamics between turnover and performance. Our reliance on Morningstar assigning accurate benchmarks may overlook subtleties that more specialized benchmarks could reveal, potentially affecting the turnover-performance relationship.

We do not account for changes of fund managers. It is plausible that fund turnover may significantly fluctuate due to changes in fund management. New managers can bring different investment philosophies and strategies, leading to shifts in turnover that reflect their personal style, rather than the inherent characteristics of the fund or its sector. Clare et al. (2014), argue that high performing funds struggle to replace skilled managers, while bad performers are more successful at replacing bad managers. Changes in management, when not controlled for, may consequently skew our results.

Lastly, our study lacks taking the fees charged upon investors into consideration. We did not control for fees due to the unreliability of the expense ratio data collected by Morningstar, making the process of collecting it manual and highly time-consuming. Consequently, as gross returns suggest that active management indeed add value, the net benefit for investors will differ once the costs to the fund managers are taken into consideration. Hence, we cannot examine whether there is a relationship between the skill of fund managers, and the fees that are charged upon investors.

# 8 Conclusion

Our analysis, consisting of 216 equity-only funds from 2000 to 2022, reveals a significant positive relationship between trading activity and subsequent returns. The relationship is particularly pronounced in funds investing across multiple markets, compared to those focusing on a single market. Within-sample evidence points to small funds, and those primarily investing in mid-cap stocks, displaying superior levels of skill. Importantly, our analysis passes a placebo test, where we replace the active funds used in the main analysis with passive index funds. Using index funds results in an insignificant relationship between turnover and performance, strengthening our main results. The main results with an unconditional analysis of skill using the full sample are, when controlling for two-way fixed effects, affected to a degree that indicates some confounding of the relationship caused by aggregate variables, an effect not observed by Ľuboš Pástor and Taylor (2017), which might be a consequence of our sample being substantially smaller.

Examining the horizon effects on our results, reveals that the payoff realization time differs between multi- and single-area funds, where single-area funds have a stronger turnover-performance relationship without a time-lag on turnover. This is one of the main findings in our paper, as it identifies that the model tying turnover to performance, might require different time-lengths between trading and its subsequent payoff, conditional on a fund's investment strategy. Funds investing in a single country display a shorter payoff structure, compared to those active in multiple areas, which might be a consequence of differing investment strategies between the two fund groups. Our results are robust to more strict clustering of standard errors and are subject to small changes when controlling for finite sample bias.

Our findings have significant implications for the role of active fund management. The demonstrated skill of fund managers in generating excess returns as a result of informed trading decisions, creates a valid argument for their role in the market environment. The variation in performance based on fund size and investment focus, provides valuable insights into the dynamics of fund management, and are in line existing literature that find small funds better suited to implement their trading strategies, and how scaling successful investment strategies as a fund grows is difficult[36].

For future research it would be interesting to examine how our results are affected when taking trading costs faced by investors into consideration. It would also be interesting to see how our finding of current turnover as a predictor of subsequent return, would perform when formalized in e.g., a long/short trading strategy, where one finances the investment in funds with high turnover, by going short in funds with the lowest turnover. Finally, a more granular analysis into the drivers of fund turnover, with higher resolution data, could uncover more detailed mechanisms behind fund performance and market dynamics, especially when trying to capture the drivers of turnover. Such research would not only extend the understanding of active fund management, but also contribute to the broader research on market efficiency and the effects of investment strategies.

This study adds to the existing body of research regarding Norwegian mutual funds and provides several novel insights into the segment of actively managed funds with ongoing operations in Norway. Our findings contribute to the ongoing debate on the efficacy of active fund management, by demonstrating the skill of these mutual fund managers, and how it varies for different fund characteristics. The robustness of our findings, despite various tests and limitations, supports the role of active management in financial markets. As the investment landscape continues to evolve, further research in this area remains both necessary and interesting.

[36](Pollet & Wilson, 2008)

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# Appendices

## A Funds

**Table A.1:** List of Funds

The table shows the list of all Norwegian actively managed mutual funds that are used in the study, both operational and discontinued.

| | |
|---|---|
| Alfred Berg Aktiv C (NOK) | Nordea Norge Pluss |
| Alfred Berg Aktiv II | Nordea Norge Verdi |
| Alfred Berg Gambak C (NOK) | Nordea SMB |
| Alfred Berg Glb Deepwater Energy | Nordea Stabile Aksjer Global Etisk |
| Alfred Berg Global C (NOK) | Nordea Vekst |
| Alfred Berg Humanfond C (NOK) | Norne Aksje Inst |
| Alfred Berg Nordic Best Selection | Norse Trend Europa |
| Alfred Berg Nordic Gambak C (NOK) | Norse Trend Global |
| Alfred Berg Norge + | Norse Trend USA |
| Alfred Berg Norge C (NOK) | Norse Utbytte |
| Alfred Berg Norge Etisk | ODIN Aksje C |
| Borea Global Equities | ODIN Emerging Markets C NOK |
| Borea Utbytte | ODIN Energi C |
| C WorldWide Asia A | ODIN Europa C NOK |
| C WorldWide Emerging Markets | ODIN Europa II |
| C WorldWide Globale Aksjer | ODIN Europa SMB |
| C WorldWide Globale Aksjer Etisk | ODIN Finland C |
| C WorldWide Healthcare Select | ODIN Finland II |
| C WorldWide Norden | ODIN Global C NOK |
| C WorldWide Norge | ODIN Global II |
| C WorldWide Stabile Aksjer | ODIN Global SMB |
| Carnegie Worldwide Emerging Growth | ODIN Norden C NOK |
| DNB Aksjefokus | ODIN Norden II |
| DNB Aktiv 100 A | ODIN Norge C NOK |
| DNB Asia | ODIN Norge II |
| DNB Europa (I) | ODIN Sverige C NOK |
| DNB Europa (II) | ODIN Sverige II |
| DNB Finans A | ODIN USA A NOK |
| DNB Global | Omega Global |
| DNB Global (III) | PLUSS Aksje |
| DNB Global (V) | PLUSS Europa Aksje |
| DNB Global A | PLUSS Markedsverdi |
| DNB Global Eiendom | PLUSS USA Aksje |
| DNB Global Eiendom (I) | PLUSS Utland Aksje |
| DNB Global Emerging Markets A | PLUSS Utland Etisk |
| DNB Global Etisk (IV) | Pareto Aksje Norge I |
| DNB Global Etisk (V) | Pareto Global C |
| DNB Global Lavkarbon A | Pareto Investment Fund A |
| DNB Global Selektiv (I) | Pareto Nordic |
| DNB Globalspar | Pareto Nordic Value A |
| DNB Grønt Skifte Norden A | SKAGEN Focus A |
| DNB Health Care A | SKAGEN Global A |
| DNB Japan | SKAGEN Insight A |
| DNB Miljøinvest A | SKAGEN Kon-Tiki A |
| DNB Norden (II) | SKAGEN Select 100 |
| DNB Norge (Avanse I) | SKAGEN Vekst A |
| DNB Norge (I) | SKAGEN m2 A |
| DNB Norge (III) | SPV Aksje |
| DNB Norge A | Sbanken Framgang Sammen |
| DNB Norge Selektiv (II) | Sigma Energy |
| DNB Norge Selektiv C | Sigma Global Explorer |
| DNB Private Banking Premium 100 A | Sigma Life Sciences |
| DNB SMB A | Sigma Nordic |
| DNB Teknologi A | SpareBank 1 Norge Verdi A |
| DNB Telecom A | SpareBank 1 Utbytte C |
| DNB Øst-Europa | SpareBank 1 Verden Verdi A |
| Danske Invest Horisont Aksje | |

# B Turnover by Fund Categories

**Figure B.1:** Co-Movement in Turnover from 2000 to 2022 by Fund Categories

Figure B.1 shows the average level of turnover for funds grouped by the Morningstar Style Box dimensions from section 5.2 and by fund size terciles in the period from 2000 to 2022 and illustrates the co-movement in Turnover for the different groups through time. Figure A: The average turnover by Stock Size categories. Figure B: The average turnover by Equity Type categories. Panel C: The average turnover by Fund size terciles.

Figure A: Average Turnover by Stock Size Category

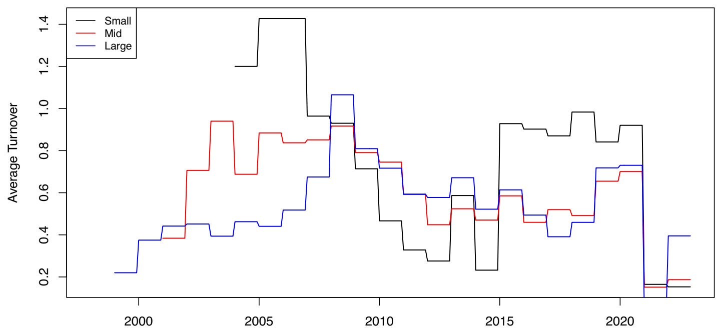



Figure B: Average Turnover by Equity Type Category

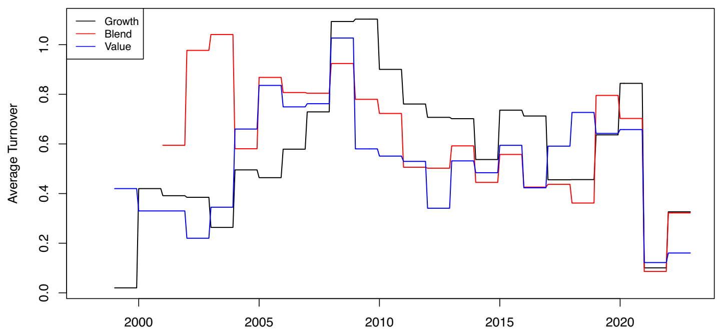
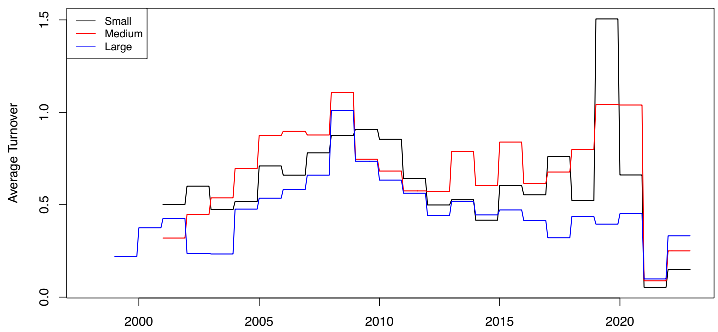



Figure C: Average Turnover by Fund Size Category



# C Variation Inflation Factor

The Variance Inflation Factor (VIF) is a measure of how much the variance of an estimated regression coefficient is increased due to multicollinearity.

The VIF for the $j^{th}$ predictor is calculated as:

$$VIF_j = \frac{1}{1 - R_j^2} \tag{C.1}$$

where $R_j^2$ is the coefficient of determination of a regression of the $j^{th}$ predictor on all the other predictors.

**Results**

**Table C.1:** VIF Test on Mispricing Proxies

Below are two tables showing the results from a VIF test on mispricing proxies that are used as independent variables in regression models where $Turnover_t$ is the dependent variable. The left and right table concern the mispricing proxies that apply for funds with a global and Norwegian investment area, respectively. The left column in each table denotes the mispricing proxy, while the right column denotes their respective variation inflation factor (VIF).

Global

| Predictor | VIF |
|---|---|
| Liquidity | 1.34 |
| Sentiment | 1.89 |
| Distress Risk | 1.76 |
| Volatility | 1.22 |

Norway

| Predictor | VIF |
|---|---|
| Liquidity | 1.92 |
| Sentiment | 1.75 |
| Distress Risk | 1.87 |
| Volatility | 1.43 |

VIF $\geq$ 2.5 is considerable multicollinearity (Johnston et al., 2018) .

# D Placebo Test

**Table D.1:** Turnover-Performance for Index Funds

The table show regression outputs of the turnover-performance relationship using Norwegian Index funds as the "placebo" group. The dependent variable is benchmark-adjusted return $R_t$ for all models, and the first row has $Turnover_t$ as independent variable, and the second has $Turnover_{t-1}$ as the independent variable. T-statistics are enclosed in () below coefficients.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | *Benchmark-Adjusted Return* | | | |
| $Turnover_t$ | 0.00010 | 0.00009 | 0.00003 | 0.00004 |
| (t-statistic) | (1.49) | (1.37) | (1.08) | (1.55) |
| $Turnover_{t-1}$ | 0.000003 | -0.000001 | 0.00001 | 0.00004 |
| (t-statistic) | (0.04) | (-0.01) | (0.39) | (0.98) |
| Month fixed effect | No | No | Yes | Yes |
| Fund fixed effect | No | Yes | No | Yes |
| *Note:* | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 | | |

# E Horizon Effects

**Table E.1:** Horizon Effects in the Full Sample

The table shows the coefficients of five regressions, indexed by columns (1) - (5). All regressions have the benchmark-adjusted return $R_t$ as the dependent variable and include both Fund-Fixed Effects. For each row the time-lag on the independent variable Turnover increases with 1 year. T-statistics are reported below each coefficient enclosed by ().

| | *Dependent variable:* | | | | |
|---|---|---|---|---|---|
| | *Benchmark-Adjusted Return* | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| $Turnover_t$ | 0.00120** | | | | |
| | (2.17) | | | | |
| $Turnover_{t-1}$ | | 0.00182*** | | | |
| | | (2.77) | | | |
| $Turnover_{t-2}$ | | | 0.00001 | | |
| | | | (0.01) | | |
| $Turnover_{t-3}$ | | | | -0.00034 | |
| | | | | (-0.71) | |
| $Turnover_{t-4}$ | | | | | 0.00007 |
| | | | | | (0.13) |
| Observations | 20,898 | 20,299 | 19,011 | 17,156 | 15,336 |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 | | | | |

**Table E.2:** Horizon Effects by Fund Category

Table E.2 shows the regression outputs of the Turnover-Performance relationship grouped by the Morningstar Stylebox and Fund Size. For all four panels the dependent variable is the Benchmark-Adjusted Return and independent variable $Turnover_t$. The regression specification is the same for all and uses Fund-Fixed Effects. The standard errors are robust, clustered by time and Morningstar Category Index. Panel A shows the regression outputs for funds grouped by Stock Size Category. Panel B shows the regression outputs for funds grouped by Stock Type Category. Panel C shows the regression outputs for funds grouped by their Fund Size Category. For all panels the t-statistics are enclosed by () below coefficients.

| | *Dependent variable: Benchmark-Adjusted Return* | | |
|---|---|---|---|
| | Panel A: Stock Size Categories | | |
| | Small Cap | Mid Cap | Large Cap |
| $Turnover_t$ | -0.00042** | 0.00224** | 0.00100 |
| *(t-stat)* | (-2.01) | (2.29) | (1.16) |
| | Panel B: Stock Type Categories | | |
| | Growth | Blend | Value |
| $Turnover_t$ | 0.00310*** | 0.00134* | -0.00040 |
| *(t-stat)* | (3.67) | (1.95) | (-0.63) |
| | Panel C: Fund Size Categories | | |
| | Small | Medium | Large |
| $Turnover_t$ | 0.00165 | 0.00099 | 0.00124* |
| *(t-stat)* | (1.35) | (1.37) | (1.69) |
| *Note:* | | | *p<0.1; **p<0.05; ***p<0.01 |

# F Finite Sample Bias

**Table F.1:** Testing For Finite Sample Bias

Table F.1 shows the results of four regressions with different specifications, indexed by columns (1)-(4). The dependent variable is benchmark-adjusted return $R_t$. The main independent variable in each model is lagged turnover $Turnover_{t-1}$. $R_{t-1}$ and $R_{t-2}$ are control variables, which are excess returns with 1 and 2 years of lag, respectively. The columns indicate which regression specification is used, with regards to month- and fund-fixed effects. T-statistics are enclosed by () below the coefficients.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | *Benchmark-Adjusted Return* | | | |
| | (1) | (2) | (3) | (4) |
| $Turnover_{t-1}$ | 0.00086** | 0.00166** | 0.00069** | 0.00098* |
| | (2.28) | (2.33) | (2.05) | (1.72) |
| $R_{t-1}$ | -0.02570 | -0.03581* | -0.04280** | -0.05330*** |
| | (-1.30) | (-1.86) | (-2.13) | (-2.68) |
| $R_{t-2}$ | -0.00660 | -0.01513 | -0.01200 | -0.02133 |
| | (-0.32) | (-0.74) | (-0.72) | (-1.28) |
| Month fixed effect | No | No | Yes | Yes |
| Fund fixed effect | No | Yes | No | Yes |
| Observations | 18,126 | 18,126 | 18,126 | 18,126 |
| *Note:* | | | | *p<0.1; **p<0.05; ***p<0.01 |