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Scale, Skill and Returns

An empirical study of returns to scale in the Nordic mutual fund industry

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Abstract

This study investigates how fund size and industry size affects the performance of Nordic mutual funds. While the effects of scale in the mutual funds industry has been widely studied in the US, literature specific to the Nordics is scant. Because of this we motivate our hypotheses using existing literature from US markets and investigate this in the Nordics. We begin by sampling 638 actively managed mutual funds that invest in the Nordic mainlands from 2008-2022. After cleaning the data, we apply fund fixed effects and a recursive demeaning procedure to eliminate the omitted variable bias and the finite sample bias. Using this we can investigate the effects of scale and skill in a bias-free setting using multivariate panel regressions.

We find empirical evidence of decreasing returns to scale at the industry level. As the size of the mutual funds industry increases in relation to the market capitalization, the ability of a single fund to outperform its designated benchmark decreases. Using the enhanced recursive demeaning estimator from Zhu (2017), we also find empirical evidence of decreasing returns to scale at the fund level. As the size of a single fund increases, its ability to outperform its designated benchmark declines. We also investigate this for each country separately. Every country apart from Denmark shows industry decreasing returns to scale, while every country apart from Sweden shows decreasing returns to scale at the fund level.

Next, we investigate the determinants for decreasing returns to scale. We find evidence that funds with a higher turnover-ratio, small-cap trading funds and funds which take more risk are more prone to decreasing returns to scale at the fund level. The evidence is in line with the theory of liquidity constraints from Berk and Green (2004). We could however not find any evidence of these determinants at the industry level. Finally, controlling for the effects of scale we investigate skill in the Nordic mutual fund industry. Our study shows that the Nordic mutual funds industry is skilled, and that skill increases over time. However, because of an increasing industry size, and an increase in the average fund size this has failed to translate into higher benchmark-adjusted returns.

Keywords – Nordics, skill, mutual funds, active management, decreasing return to scale, recursive demeaning, fixed effects, fund size, industry size

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1 Introduction

Is bigger always better? In many industries, size comes with advantages. But did you know size could have adverse effects for mutual funds? In this study, we will examine how the performance of fund managers in the Nordic countries is affected by increased fund and industry size.

Many previous studies have considered the size-performance relationship for mutual funds. Most of these studies conclude that as size increases, the performance of a fund goes down. This mechanism is often referred to as 'decreasing return to scale'. Decreasing returns to scale can occur at both the fund and industry level. That is, as the size of a fund increases its ability to generate returns is reduced, as shown by Zhu (2017). Alternatively as the size of the surrounding industry increases the ability of a single fund to generate returns is reduced, as shown by Pástor and Stambaugh (2012).

The literature provides liquidity constraints as the primary explanation for decreasing returns to scale at both the industry and fund-level. With an increase in fund size, the fund trades larger quantities, causing larger adverse price movements in the underlying security. For industry size, an increase means there is more competition in the market, removing mispriced securities the fund could have exploited. By being publicly available, actively managed funds are capable of attracting large amounts of capital in a short period of time. In fact, the fund's size can become so large that it may potentially disrupt its own performance at a certain point. In these cases, funds may have simply outgrown their investment strategies, and fund managers potentially find themselves in a situation where they need to adapt to a different strategy.

The concept of 'decreasing return to scale' has primarily been researched in larger markets such as the United States (US) market, while it is less studied in the Nordics. Compared to the actively managed fund market in the US, the Nordic countries consist of few funds, making it difficult to obtain enough observations for each to be individually representative while being statistically significant. For this reason, we define the Nordic market by combining fund observations from Norway, Sweden, Denmark, and Finland in the time span of 2008 to 2022. Although the countries may behave differently at times, we obtain exciting results that can explain the Nordic relationships related to return to scale.

An important aspect of the thesis is to define the investment area of the funds. Since we are looking at how the sizes impact the funds performance, we also include foreign funds that could impact sizes within the market. Before any additional screening and data cleaning, we have a data sample of 638 actively managed mutual funds which invest in the Nordic mainlands.

Throughout our study, we draw inspiration from and compare our results to Pástor et al. (2015), who conducts a similar study in the US market. Building our thesis upon their methodology, we utilize OLS with fixed effects (FE) and recursive demeaning (RD), to counter the omitted variable bias and the finite sample bias. In addition we introduce the enhanced recursive demeaning estimator (RD2) from Zhu (2017) to correct for a misspecification with the original RD estimator. For industry size we use FE methodology, while we use RD for fund size.

In the analysis, we start by examining the fund size to performance relation. We show results based on different estimators to highlight potential econometric pitfalls and how we avoid these. Beginning with the OLS estimator we obtain a significant positive coefficient, which indicates an increasing return to scale. However, because of the omitted variable bias arising from cross-sectional difference in fund skill, we proceed to the FE estimator. As expected, this results in a statistically significant negative coefficient, indicating decreasing returns to scale. However, FE can lead to spurious results due to the finite sample bias. Therefore we move on with the RD estimator. Unfortunately, this estimation does not yield statistically significant results.

For industry size we can tell a different story. Using OLS we get results that are strong both statistically and economically. In addition, using both FE and RD regressions shows industry size to be both economically and statistically significant. However, industry size is not likely to be biased using FE, which means FE is the preferable methodology when fund size is not used. Either way, our findings indicate a decreasing industry returns to scale at the industry level.

After running all estimates for industry size and funds size we look at a potential correction for misspecification using the enhanced RD estimator (RD2) from Zhu (2017). When switching from the original RD estimator to the enhanced one, the coefficient for fund size flips back to negative while being statistically significant, indicating a decreasing return to scale. Given both empirical and theoretical backing for the RD2 estimator, we use this going forward. Using correct methodologies we find that a 10 million dollar increase in fund size reduces excess return by -0.003%. At the same time, a 1% increase in industry size reduces excess returns by -0.104%.

As results indicate decreasing return to scale in the Nordics, we apply controls to each variable of interest to back up the results. We carefully apply variables which can be argued to omitted. For fund size, the controls includes: family size, sector size, turnover ratio, fund age and manager experience. Fund size shows to be robust for all specifications that do not suffer from a large loss of observations. Controlling for industry size, the chosen control variables are average fund size, number of funds, and sector size. Two dummy-variables are also used for 2008 and 2020 to pick up any abnormal noise from the financial crisis and the recent pandemic. Industry size remains robust in all specifications. During this process we also find evidence of a negative size-performance relationship for family size and sector size. In addition, performance goes down with age even when controlling for size.

Since the Nordic market is a combination of individual funds, we could get results that are skewed if one or more countries drags the result in a certain direction. We therefore take a closer look at each sampled country and determine if they share enough characteristics to be defined as a market and whether they experience the same excess return. The results from this shows every country apart from Denmark have decreasing return to scale at the industry level, while every country apart from Sweden have decreasing return to scale at the fund level. We connect this to a quintile regression of fund size, showing that the largest funds actually have increasing returns to scale. Since Sweden has the largest average fund size of the sample, and Finland amongst the lowest, we explore this possible explanation.

Having shown a decreasing return to scale relationship both on the fund and industry level in the Nordics, we now test the determinants of decreasing returns to scale. That is, if small-cap funds and funds with high turnover ratio are more prone to the effects of decreasing return to scale. Here we use interaction terms with fund size and industry size. The results shows that the negative size-performance relation for fund size is steeper for funds which invests in small-cap stocks, have a higher turnover and take greater risks. The evidence coincides with Berk and Green (2004)'s theory of liquidity constraints. We could not find any evidence for the determinants of industry size.

Finally, we take a closer look at the effects of scale on skill in the Nordic mutual industry. Results show that the skill increases over time. When controlling for scale skill Nordic mutual funds manager produce an excess return of about 0.25%. This increases to about 0.36% at the end of our time-series. However, since both the industry size and the average fund size also increases over time, this does not translate into higher benchmark-adjusted excess return, because of decreasing returns to scale.

2 Literature review and hypothesis

2.1 Literature on scale and skill

Before conducting our analysis we explore the existing literature on the topics of scale and skill. This section looks at the study we are replicating as well as other relevant articles in the same space. The final aim is to give an insight into where our methodology and results fit within existing literature. Both where it converges, and perhaps more importantly, where it differs.

2.2 Pástor et al. on scale

Our study replicates the methodology and main analysis of Pástor et al. (2015) in Nordic markets. The article samples US equity mutual funds who invest domestically and looks at the size-performance relation on a fund and industry-level, as well as skill. This is motivated by articles such as Berk and Green (2004) on fund-size, while Pástor and Stambaugh (2012) motivates the size-performance relation on an industry level. Further, they resonate that if performance is impacted by scale - one must understand the effects of scale before one can understand skill.

Pástor et al. (2015) report two main findings: decreasing returns to scale at the industry level and increasing skill over time in US-markets. However, with an increasing industry size during their time-series and diseconomies of scale, the increase in skill does not translate into an increased excess return. The article does not find a statistically significant size-performance relationship for fund size in specifications which controls for biases. However, it should be noted that they do find statistically significant relationships when using an OLS estimator and OLS with fixed effects.

2.2.1 Other literature on fund size and its determinants

There is a large body of work on fund size. Berk and Green (2004) make a theoretical argument for decreasing returns to scale. The idea is that some managers are more skilled than others and generate higher returns. When observed by investors, this causes an increase in fund-flows which hampers the managers ability to generate returns and utilize their skill. It should be noted already here, that the investors of Berk and Green (2004) can not observe the true skill of the fund, but rather they "perceive skill". Their perception is based on the sum of both the true skill of the fund as well as random outperformance which makes the fund appear skilled (noise).

Berk and Green (2004) puts forth liquidity constraints and market impact as the explanation for decreasing returns to scale. In their model, managers utilize their knowledge to pick underpriced securities and earn a higher return. The underpriced securities are often small-cap stocks with limited liquidity. As the fund grows larger, the manager can no longer rely on such trades without adversely impacting the price of such stocks. To maintain a high return, the manager would now have to find many such trades. In essence, the manager's skill is spread too thin and returns decline. Henceforth we refer to this as the "theory of liquidity constraints". Over the long run the model implies equal performance among mutual funds even when skills differ, since any difference in skill would increase fund flows and lower returns.

Several articles explore the size-performance relation empirically. Among others Chen et al. (2004), Indro et al. (1999), Yan (2008) and Ferreira et al. (2012). All of which establish a statistically significant, inverse relationship between fund size and performance for US markets.[1] It should however be noted that these apply a different methodological approach to that of Pástor et al. (2015). The listed articles use pooled OLS while employing different controls. For example, Chen et al. (2004) notes the bias arising from cross-sectional fund characteristics. They further note that fixed effects would have solved this, but choose not to use it because of the regression-to-the-mean bias.[2] Their solution is to use factor models, while including variables such as turnover, fund age and family size as controls. However, to our understanding none of these articles discuss or account for the cross-sectional differences in skill. Though we will use a different methodological approach, our first hypothesis will be in line with the existing literature:

[1]We may also note some articles more critical to the effects of fund size such as Phillips et al. (2018) and Adams et al. (2019). It is still our impression that the overall literature heavily favors decreasing returns to scale.

[2]This is equivalent to what we will call the "finite sample bias".

"Nordic funds show decreasing returns to scale at the fund level"

The empirical literature also provides some proof on the determinants of decreasing returns to scale at the fund level. Both Chen et al. (2004) and Yan (2008) find that decreasing returns to scale is more pronounced for small-cap investing funds. The latter also finds that funds with a high turnover exhibit steeper decreasing returns to scale. Once we connect this to Berk and Green (2004) a story emerges from the overall literature backed by both theoretical and empirical evidence. There seems to exist an inverse relationship between size and performance. As funds grow larger their ability to pick underpriced, small-cap securities is hampered by at least two different mechanics. Either the fund must now find numerous such securities to maintain returns, thereby spreading their skill too thin. Alternatively they must continue to trade the same securities at a larger volume, with a larger negative price impact. Because of this, we expect steeper decreasing returns to scale for small-cap trading funds and funds with a high turnover ratio. Given the convergent nature of the literature on the determinants, we define our next hypothesis as:

"The determinants of decreasing returns to scale at the fund level are consistent with the theory of liquidity constraints from Berk and Green (2004). This implies funds with a higher turnover ratio and which have a strategic focus on small-cap stocks exhibit steeper decreasing returns to scale at the fund level."

2.2.2 Other literature on industry size

Industry size and its competitive effects has also been studied. Hoberg et al. (2017) finds evidence that with more rivals in a funds "style" (sector), the funds alpha may dissipate. Pástor and Stambaugh (2012) argue that industry decreasing returns to scale is not only a feature of the mutual fund industry, but an explanation for the popularity of mutual funds despite their poor recent track records. In their model, investors both believe in industry decreasing returns to scale, and they are slow to update their beliefs about it. This results in a slow decline despite poor performance. We can also view this in relation to Berk and Green (2004). The investors of Pástor and Stambaugh (2012) observe the returns of the industry and perceive this as skill. They then allocate capital to the mutual funds industry based on their perception of its overall skill.

Ferreira et al. (2012) runs regressions including industry size, much in the same way as Pástor et al. (2015). The article shows decreasing returns to scale at the indusry level, for both US and non-US equity funds. Given both theoretical and empirical backing of the results from Pástor et al. (2015), our hypothesis about industry size will be:

"Nordic funds show decreasing returns to scale at the industry level"

Ferreira et al. (2012) take their conclusion further by stating that there are fewer unexploited mispricing opportunities in countries with larger mutual fund industries. This can be connected back to the theory of liquidity constraints. Either the fund's own size increases so that they can no longer effectively exploit mispriced smaller stocks, or the industry size increases so the mispricing opportunities are lost due to competitive effects. Again we expect this to have a larger impact on small-cap trading funds and those with a high turnover ratio. Because of this, we formulate the next hypothesis:

"The determinants of decreasing returns to scale at the industry level are consistent with the theory of liquidity constraints from Berk and Green (2004). This implies funds with a higher turnover ratio and which have a strategic focus on small-cap stocks exhibit steeper decreasing returns to scale at the industry level."

2.2.3 A closer look at the Nordics

While the literature on fund size in the US converges on several points, the literature covering other parts of the world does not tell the same story. As mentioned, Ferreira et al. (2012) find decreasing returns to scale at the fund level for US domestic funds. The same study also extends to US international funds and non-US domestic funds. Both of which show increasing returns to scale. For US international firms, this could be viewed as further evidence for the theory of liquidity constraints. Since international funds are not limited to the possibilities of their home market, they do not lose investment opportunities due to liquidity as they grow larger. Since non-US domestic funds also show increasing returns to scale this should make us somewhat skeptical of the first hypothesis. However, considering the vast number of countries included in Ferreira et al. (2012), which may vary greatly from the Nordic countries we keep the original definition.[3]

Literature specific to the Nordics is scant. The only published article we could find is Dahlquist et al. (2000) from which the results are somewhat mixed. Decreasing returns to scale are only found for "*Allemansfonder*" which is part of a public savings program. The study finds no significance for regular mutual funds. In addition the study is specific to the Swedish market. Johansson and Jacobsson (2012) also looks at size in the Swedish markets with very few statistically significant results. However, both a very small sample size of 91 funds, and the fact that the study is a master-thesis (unpublished) causes us to be somewhat careful with the article. Given the low amount of evidence for the Nordic region, this motivates our previous hypotheses. With little reliable evidence to the contrary we also define our next hypotheses as:

"When looking at each sampled country in the mainland Nordic region, each country exhibits decreasing returns to scale on the fund level."

"When looking at each sampled country in the mainland Nordic region, each country exhibits decreasing returns to scale on the industry level."

2.2.4 A closer look at skill

Fama (1970) propose the efficient market hypothesis (EMH) which can help conceptualize skill's role in financial markets. The model considers markets as either strong, semi-strong or weak-form. For a market to be considered strong-form, prices must "*fully reflect*" all available information. When this is the case, the market is efficient. In such a market, skill is not necessarily non-existent, but rather not useful since there would be no mispriced

[3]Specifically, they may vary greatly in terms of liquidity. We have already shown, and will show even clearer later on why this is important.

securities. Indeed a lot of the literature seems to support this empirically. Amongst others, Horne and Parker (1967) provides empirical evidence of random stock movements. This serves as evidence that stock prices are only affected by new and unpredictable information. In other words, all available information is already reflected in the price. Carhart (1997) provides evidence from the fund-side showing that mutual funds are not persistent over time.

However, even Fama (1970) states that strong-form efficiency is unlikely to be a realistic depiction of financial markets. There is also empirical evidence against markets being efficient. Bondt and Thaler (1985) show that markets overreact to unexpected and dramatic news events. Haug and Hirschey (2006) show the "*January effect*", where returns are systematically higher in the month of January. Both articles can be viewed as contradictory to the efficient market hypothesis. As one can see, some of the evidence indicates that markets are not fully efficient. The point of this section so far is to answer this question: If we believe there are mispriced securities and that strong form EMH doesn't hold - should not the most skilled funds be able to capitalize on this and beat the market?

Fama and French (2010) finds that while funds might beat the market, few have sufficient skill to cover the cost of fees. While comparable studies find similar results, these studies often use factor loadings to control for relevant risks. Over time these models have been finessed more and more, and the literature seemingly always finds some risk-factor which is not accounted for. However, the overall conclusion from the literature is that mutual funds do not show persistence.

This might not be the case for Nordic funds however. Vidal-García et al. (2023) finds evidence of persistence for Scandinavian Mutual Funds. Järf (2016) finds the same for Nordic markets, though the results are somewhat mixed. The article finds that the smallest countries show the greatest persistence, speculating that the market will move closer towards efficiency in the future. For our study the most relevant part is this: there are likely mispriced securities in the market, but whether skill can translate this into benchmark adjusted excess return is open to question.

To get a final view of skill, we must connect it to Berk and Green (2004) and Pástor et al. (2015). The investors of Berk and Green (2004) can both observe and act on information of perceived skill. As mentioned previously, this changes fund-flows which again lowers returns. As Pástor et al. (2015) states, we can not understand skill without looking at the impact of size. Therefore we define our next hypothesis in line with the findings of Pástor et al. (2015) of increase skill over time in US market:

"Nordic funds show increasing skill over time when controlling for the effects of scale."

2.2.5 Hypotheses

To summarize, we now structure our hypotheses in the order they are discussed in the analysis.

1. *Nordic funds show decreasing returns to scale at the fund level.*
2. *Nordic funds show decreasing returns to scale at the industry level.*
3. *When looking at each sampled country in the mainland Nordic region, each country exhibits decreasing returns to scale at the fund level.*
4. *When looking at each sampled country in the mainland Nordic region, each country exhibits decreasing returns to scale at the industry level.*
5. *The determinants of decreasing returns to scale at the fund level are consistent with the theory of liquidity constraints from Berk and Green (2004). This implies funds with a higher turnover ratio and which have a strategic focus on small-cap stocks exhibit steeper decreasing returns to scale at the fund level.*
6. *The determinants of decreasing returns to scale at the industry level are consistent with the theory of liquidity constraints from Berk and Green (2004). This implies funds with a higher turnover ratio and which have a strategic focus on small-cap stocks exhibit steeper decreasing returns to scale at the industry level.*
7. *Nordic funds show increasing skill over time when controlling for the effects of scale.*

2.3 Our contribution

Our thesis contributes to the existing research in several ways. First and foremost it provides empirical evidence of the size-performance relation at both the industry and fund level. This topic has been thoroughly researched for US markets. However, to our knowledge, no other study has scale as their main topic of research for Nordic markets. Our thesis is also the first in the Nordics to consider the effects of scale using a bias-free methodology to account for cross-sectional variation in skill. Second, we provide empirical evidence on the determinants of the scale-performance relation in the Nordics. Third, using our findings on scale and its determinants we are able to explore skill while controlling for the effects of scale. This gives a unique insight into the Nordic markets, which we then compare to the far more studied US market.

3 Methodology

In this section we follow the methodology of Pástor et al. (2015) and Zhu (2017). We choose to give a comprehensive explanation of the methodology and try to spell it out intuitively. This makes the following section somewhat long and in-depth. In addition some parts may seem repetitive because they explain closely-related topics, but based on different equations, assumptions or models. However, as we will see, choice of estimator is extremely important, which motivates our somewhat lengthy explanation.

We explore two econometric biases and their respective solutions. The first is the omitted variable bias, which is solved by introducing the fund fixed effects estimator (FE).[4] This in turn creates a second bias known as the finite-sample bias from Stambaugh (1999). We will solve this bias by including a recursive demeaning estimator (RD) from Hjalmarsson (2010). Finally, given a potential misspecification in Pástor et al. (2015), we implement an enhanced estimator (RD2) from Zhu (2017). But first, we take a look at why we choose to benchmark-adjust our returns.

3.1 Benchmarking vs Fama-French and others

A common approach to adjust for risk and investment style is to look at different factor loadings and the excess return, or “alpha” once adjusting for this. The literature is rich with methods to achieve this. Most famously we have Fama and French (1993) which propose a three factor model. Our approach is far more straightforward, simply taking return in excess of a relevant benchmark as selected by MSD. We harbor support for this approach from Cremers et al. (2010) which illustrates the bias in both Fama-French and Carhart models. It also concludes that benchmarking is preferred to factor models in obtaining excess return. Based on this advice our method seems both more practical, realistic and less prone to bias. It does however require that comparable benchmarks are chosen, but we entrust the professionals at MSD to achieve this. As discussed in the data section however, some benchmarks have been manually applied. We believe this to be

[4] Going forward, we will often refer regressions using OLS with fixed effects as simply "FE" to save space.

largely unproblematic as we have followed the same methods used by MSD to apply these benchmarks.[5]

3.2 The unobservable skill and the omitted variable bias

1. $R_{it} = a + \beta q_{it-1} + \epsilon_{it}$

In its simplest terms, the model of interest is eq.1, excluding controls for now. We measure R_{it} as the benchmark adjusted gross return of fund i in period t, and q_{it-1} as the funds size in the previous observed period. Using this equation however has two problems which are both related to the skill of fund managers. The first is the unobservable nature of skill and the second the is omitted variable bias this causes.

The unobservable nature of skill is well documented in the literature. Amongst others it is discussed by Fama and French (2010), which looks at the struggle to distinguish luck from skill. In our context, any macro-factor that affects the return of a given fund should be controlled for by taking the return net of a relevant benchmark. Then, if we observe a movement in return, we have no way of knowing whether it has been affected by a manager's skill or is simply down to luck. Because of this we are unable to include skill into our model to control for it.

Therefore, in eq.1 it is unlikely that size is determined exogenously. Factors such as marketing, brand recognition and perceived manager skill could change the flow to a specific fund. This is especially relevant for skill, which arguably is both correlated to q_{it} and a determinant of R_{it} while remaining unobserved. For example, if a manager is more skilled than his peers, they will generate a higher return which in turn is likely to attract larger fund flows increasing size for the next period. When this is the case we have a violation of the zero conditional mean assumption through an omitted variable bias. The zero conditional mean requires that the expected value of the error term is zero

[5] Keep in mind that when we refer to "excess return" we mean return in excess of a benchmark, not in excess of the risk free rate.

for any value of the independent variable. Since fund size is likely affected by skill, this assumption does not hold when skill is an omitted variable.

3.3 Fund fixed effects

Though other studies have estimated the size-performance using eq.1, the previous section motivates our choice for using the methodology from Pástor et al. (2015). The next step is to apply fund fixed effects to remove the omitted variable bias from eq.1. The gives us eq.2:

2. $R_{it} = a_i + \beta q_{it-1} + \epsilon_{it}$

Skill is now dealt with by introducing funds fixed effects a_i which removes any unobserved heterogeneity from skill. In other words: using fund fixed effects allows us to look at the variation within each fund across time while ignoring the cross-sectional dimension from skill. When looking only at the change within each fund over time which, this removes the difference in skill between managers. However, it still requires the assumption that skill stays constant over time for each fund, as time-varying skill within each fund could still cause bias.

We can connect eq.2 to Berk and Green (2004). In this specification, the funds true skill corresponds to a_i. Following Berk and Green (2004), investors can not observe a_i in real time as their perception of skill also includes noise. Because of this the size of a fund, at any given time is likely "incorrect" in relation to the fund's true skill. In their model, true skill is constant while perceived skill fluctuates as investors update their perceptions of the funds skill. For example if skill is perceived to be higher than true skill by inventors, the allocated capital will be higher than what it should be given the funds true skill. Because of the negative size-performance relation future returns are expected to be lower.

Since investors can not observe true skill, they can not observe the size-performance relation in real time either. Using fixed effects however, we as ecnomometricians can identify the effect of the size-performance relation retrospectively in the context of the Berk and Green (2004) model.

We can find the OLS FE estimator (β in eq.2), from eq.3, which is a demeaned model where each fund has their full time series average subtracted. Later we will look at how this model can be biased and other methods of demeaning the data. We also show the OLS FE estimator in eq.4.

3. $\tilde{R}_{it} = \beta \tilde{q}_{it-1} + \tilde{\epsilon}_{it}$
4. $\hat{\beta}_{FE} = \left(\sum_{t,i} \tilde{q}_{i,t-1}^2\right)^{-1} \left(\sum_{t,i} \tilde{q}_{i,t-1} \tilde{R}_{it}\right)$

When using FE we cluster the standard errors by sector x month to avoid cross-sectional correlation between funds belonging to the same sector when using fixed effects. Also, to avoid serial correlation. This ensures any t-statistic shown using FE is hetereoskedasticity robust.

3.4 Finite sample bias

Using the fixed effect estimator introduces a problem of its own called the finite-sample bias as evidenced in Stambaugh (1999). This problem arises when trying to estimate eq.2 using OLS. Specifically, we get a positive correlation between the error term ϵ_{it} and the innovation in q_{it} which can lead to a negative spurious regression in finite samples. This positive correlation comes about for two main reasons:

1. Performance-flow relation: If a firm randomly outperforms one period, R_{it} increases. When observed by investors, this will likely lead to increased flow to the fund as it will be perceived as skill. Thereby increasing its net assets at the end of the period.
2. Mechanical link: When a firm randomly outperforms, it still increases the value of their holdings meaning that net assets are increased at the end of the period.

Where this correlation leads to a negative spurious regression is best exemplified by looking at a the OLS estimator in eq.2 for a single fund, $\hat{\beta}_i$. Now suppose we observe the returns of the single fund R_{it}, over two periods, while setting the fund fixed effects, a_i, as well as the estimator $\hat{\beta}_i$ to zero. Where this now becomes problematic is when $\epsilon_{i1} \neq 0$. For example, if $\epsilon_{i1} > 0$ we know that $R_{i1} > 0$, and because of the performance-flow relation and mechanical link, we know $q_{i2} > q_{i1}$. Intuitively, even when there are no direct effects from scale or other factors ($a_i = \hat{\beta}_i = 0$), we still know from above that a random overperformance will increase fund size. Keep in mind that this also works the other way. Should a fund randomly underperform, we can expect its size to decrease.

The problem in both cases is that the error term has an expected value of zero ($E(\epsilon_{i2}) = 0$). Put simply, we expect random factors to have a mean of zero the next period. Looking at a fund where in the first period $\epsilon_{i1} > 0$, in the next period we expect $\epsilon_{i2} = 0$. This means that while q_{i2} has increased from the random outperformance in the first period, its performance in the second period is expected to be zero. The regression will now interpret this as: fund size has increased while return has decreased. Conversely, a fund that decreases in size will appear to have a better performance the next period. Both instances causes a spurious regression where $\hat{\beta}_i$ appears to be negative, showing decreasing returns to scale - where there are none.

We can not however say with certainty that in the next period ($E(\epsilon_{i2}) = 0$), only that this is the expectation. Performance in the next period due to randomness is indeed random. Therefore, in an infinite sample, this does not create any problems. In an infinite sample the error term produces an infinite amount of random q_{it} which is then paired with as many high, as low values of R_{it}.[6] In our finite sample however, this is not the case. Since $\hat{\beta}_{FE} = \sum wi * \hat{\beta}_i$, the OLS FE estimator carries the weighted average of the biases explained above. The conclusion here is that our OLS FE estimator also runs the risk of a negative spurious relationship which can falsely identify decreasing returns to scale.

[6]As produced by the error term in the next period.

3.5 Recursive demeaning

The final solution to these problems is to implement recursive demeaning, which allows for fund fixed effects while avoiding the finite-sample bias. When using recursive demeaning we forward-demean excess return and the independent variables, while instrumenting for the forward-demeaned fund size by using the backward-demeaned fund-size. Here we follow the methodology of Hjalmarsson (2010) and Moon and Phillips (2000). We begin by looking at the regression equation 5. which is used for this method.

5. $\bar{R}_{it} = \beta' \bar{x}_{it-1} + \bar{\epsilon}_{it}$

In this equation, each variable is forward-demeaned as symbolized by the bar above it. Contrary to regular demeaning such as in fixed effects, we only subtract the average of all variables forward in time from the observation. The independent variable $\bar{x}_{it-1}$ represents a vector of regressors, which simply means it contains all our independent variables used for that estimation. As we can see it is also forward demeaned, but with one exception. When $\bar{x}_{it-1}$ contains the lagged fund size q_{it-1}, we instrument for $\bar{q}_{it-1}$ by using $\underline{q}_{it}$. We will explain and discuss instrumentation closer in the following section. For now we consider the equations below. The bar below a variable symbolizes that we have backward-demeaned the variable. Here we subtract all values back in time from the observation. Below we show the equations used to forward and backward demean variables following the notation used in Moon and Phillips (2000).

With $\underline{x}_{it-1}$ for $t = 2,....,T_i$, we can write the backward demeaned regressor as,

6. $\underline{x}_{it-1} = x_{it-1} - \frac{1}{t-1} \sum_{s=1}^{t-1} x_{is-1}$

Using the same logic, we can write the forward demeaned regressor as,

7. $\bar{x}_{it-1} = x_{it-1} - \frac{1}{T_i - t + 1} \sum_{s=t}^{T_i} x_{is-1}$

Also, the forward demeaned excess return can be written as,

8. $\bar{R}_{it} = R_{it} - \frac{1}{T_i - t + 1} \sum_{s=t}^{T_i} R_{is}$

When we use all these definitions in our regression model, a_i from eq.2 is removed and we are left with eq.5.

The question still remains however, how does this remove the bias? We can see this best by comparing the backward-demeaned instrument to the regular demeaning (used in FE), while using what we learned about the finite sample bias in the previous section.[7] In a regular regression, there is no correlation between q_{it-1} and ϵ_{it} (last period's size can not plausibly be affected by this period's error term). However, once the model has been demeaned for fixed effects, there will be a correlation between $\tilde{q}_{it-1}$ and $\tilde{\epsilon}_{it}$. When subtracting the mean from $\tilde{q}_{it-1}$ we are also subtracting observations after $t-1$. Should q_{it} increase in a period after $t-1$, then $\tilde{q}_{it-1}$ will decrease, and these values can be affected by $\tilde{\epsilon}_{it}$. Hence, it is negatively correlated with the innovation in q_{it}. The solution is to backward demean q_{it-1}, subtracting only observations from past periods. This removes any correlation between the variables.

The next question is then, why is only q_{it-1} backwards-demeaned? Following the logic above, variables such as turnover ratio should display the same correlation mechanics between its demeaned values and the demeaned error term. The answer is that they do indeed also display these correlation mechanics. Now we can connect it to the finite sample bias in the previous subsection. Because, without the further correlation between the innovation and the error term as described in section 3.4 this is unproblematic for the regression. To visualize this, imagine a chain of correlation for fund size. $\tilde{q}_{it-1}$ is negatively correlated with the innovation in q_{it} which in turn is positively correlated with ϵ_{it}, which is the error term for R_{it}. This link drags fund size back into the finite sample bias discussed in section 3.4 through the performance flow relation and the mechanical link. In this chain only the latter parts are problematic.

This chain must therefore be broken at some stage. For fund size we implement backwards demeaning to break the chain in its first stage. For the other variables however, there is no reason to believe that their innovations are correlated to the benchmark adjusted

[7]The following also serves as an alternative explanation for the finite sample bias, this time basing it on eq.3 instead of eq.2.

return (of a single fund). Hence, the chain is broken in the latter stage, and backwards demeaning is not necessary. For example, a random outperformance by a single fund, increasing R_{it} should not plausibly increase turnover rate or industry size in the same way as fund size.

The implementation of this is to use eq.5. Here, every variable is forward demeaned and regressed on the forward demeaned R_{it}. The exception is fund size, where $\tilde{q}_{it-1}$ is regressed on $\underline{q}_{it-1}$ to obtain fitted values. Next, the fitted values are regressed on $\bar{R}_{it}$. In both of these regressions, the intercept is excluded. This is the method used for RD in every equation which includes fund size. When fund size is not used however, we use OLS with FE (eq.2) because the finite sample bias should not be problematic for the other variables (following the discussion above). The only exception is in section 5.1 to show some of the bias. We will come back to this and be more specific about where recursive demeaning is or is not being used. To end this segment we can look at the IV estimator we have now created for fund size using RD.

9. $\hat{\beta}_{RD} = \left(\sum_{i=1}^{n}\sum_{t=2}^{T_i}\bar{q}_{it-1}\underline{q}'_{it-1}\right)^{-1}\left(\sum_{i=1}^{n}\sum_{t=2}^{T_i}\bar{R}_{it}\underline{q}'_{it-1}\right)$

In all RD specifications we cluster by fund (in addition to sector x month) to counter any potential serial correlation within funds brought on by the RD procedure. This ensures any t-statistic shown using RD is heteroskedasticity robust.

3.6 Recursive demeaning 2

In the time since Pástor et al. (2015) released their recursive demeaning estimator, some new work has been done in the field. Mainly Zhu (2017) points out two potential misspecifications in the original RD-estimator. The first occurs when excluding the intercept in the first-stage regression. This would imply that fund size moves around a constant mean over time, which both seems unlikely and is left unjustified in the original methodology. Second, Zhu (2017) use q_{it-1} as the instrument, which also avoids the finite sample bias as q_{it-1} is correlated with $\tilde{q}_{it-1}$, but uncorrelated with $\tilde{\epsilon}_{it}$ as it does not contain information from after $t-1$. In order to choose the optimal instrument however, we must further discuss instrumentation. In eq.10 we present the estimator for RD2, where $\bar{x}^*_{it-1}$ is the fitted value from the first-stage regression.

10. $\hat{\beta}_{RD2} = \left(\sum_{i=1}^{N}\sum_{t=1}^{T_i-1} \bar{q}^{*\prime}_{it-1}\bar{q}^{*}_{it-1}\right)^{-1}\left(\sum_{i=1}^{N}\sum_{t=1}^{T_i-1} \bar{q}^{*\prime}_{it-1}\bar{r}_{it}\right)$

The problem we are facing is simply endogeneity which can not be solved as skill can not be included in our model. To solve this Pástor et al. (2015) use $\underline{q}_{it-1}$ as an instrument for $\bar{q}_{it-1}$. For $\underline{q}_{it-1}$ to be a valid instrument it must fulfill two conditions according to Roberts and Whited (2013).[8]

1. Relevance requires that the instrument and the endogenous variable does not have a partial correlation which equals zero. We know this to be the case, as they are both derived from q_{it-1}. It can also be observed from table 3.1 where the slope coefficient from the first stage regression ($\bar{q}_{it-1}$ on $\underline{q}_{it-1}$) does not equal zero.
2. Exclusion requires that E$[\epsilon|\underline{q}_{it-1}] = 0$, which we know to be the case as $\underline{q}_{it-1}$ contains only backward looking information.

Zhu (2017) on the other hand use the lagged fund size q_{it-1} as the instrument. This is also likely to fulfill both conditions. It is obviously correlated with $\bar{q}_{it-1}$, which is also shown in table 3.1 as the slope coefficient is not zero. In addition it likely fulfills the exclusion condition as it does not contain information forward in time. Next, Zhu (2017) argue that by including the intercept in the first stage and by using $\bar{q}_{it-1}$ the relevance condition can be improved.

Table 3.1 shows the first stage regression for both RD1 (instrumented with $\bar{q}_{it-1}$) and RD2 (instrumented with q_{it-1}). Here we see that R-squared improves from 0.9% to 8.2% when changing our instrument to q_{it-1} and including the intercept in the first-stage. If we also keep in mind that the asymptotic variance of the estimator is given by eq.11, we realize the importance of a good fit in the first stage. As Zhu (2017) states: *"A weak*

[8]It is also common practice in econometrics to use three conditions. Robert and Whited argues that the third condition, exogeneity, should be evident once the two presented here are fulfilled.

first stage with a small R-squared value is a warning sign. At its best, it leads to a large uncertainty in quantifying the size effect. At its worst, it can cause bias and inconsistency in estimating β".

11. $\mathrm{Var}(\hat{\beta}_{\mathrm{RD}}) \propto \frac{\sigma_i}{R_i^2}$

Table 3.1: First stage regression for RD1 and RD2

	Dependent variable: Forward demeaned *FundSize*	
Variable	(1)	(2)
Instrument RD1	0.095	
	(22.28)	
Instrument RD2		0.096
		(69.76)
1.st stage intercept		-4.176
		(-35.20)
Observations	53,954	54,528
R^2	0.9%	8.2%
F Statistic	496.589***	4,866.475***

4 Data

During the process of extracting data from the Nordic fund market we make various decisions and impose certain limitations in our search to obtain relevant data for our study. In the subsequent chapter, we offer a detailed overview and explain the foundation for the data collected.

4.1 Sources and criteria

We primarily utilize Morningstar Direct (henceforth referred to as MSD) as our data provider. In instances where MSD lacks essential data, we resort to the Bloomberg Terminal as an alternative. By using the MSD database for Global Open-Ended Funds, we are able to narrow down data by using the platform's variables and criteria. Our main dataset (from MSD) consisted of 638 funds prior to the data cleaning.

We started our data collection process by excluding all non-equity funds from MSD's Global Broad Category Group. This ensures that the funds included in our dataset solely invest in equity, excluding categories such as money market funds or fixed income. Furthermore, we remove all funds with "Index Fund" or "Index" in their names to preclude any funds that are unnoticed by the MSD variable or aren't actively managed.

The time frame for our dataset spans from the start of 2008 to the end of 2022. To ensure our data remains within this frequency, we manually define each variable, such as excess return and fund size. This approach is essential to incorporate funds established before this timeframe that are active during our study. MSD's "Inception Date" data cut-off only considers funds created after a given date, which limits its scope. Consequently, our manual specification not only addresses those funds established after the given start date but also includes all funds operational within our study's timeframe.

Throughout their operational tenure, funds frequently undergo liquidation or choose to merge with other funds/fund classes. To ensure we are not losing any of the funds in our dataset due to this, we incorporate non-surviving funds through MSD's own defined criteria. This includes funds that are established prior to our selected timeframe and operated within it, but subsequently faced liquidation or a merger. This also helps us avoid survivorship bias in our analysis. Brown et al. (1992) and Elton et al. (1996) extensively discuss the importance of recognizing survivorship bias in financial analysis. Excluding funds that fade away due to poor performance can lead to a dataset skewed towards funds that generally perform better. Therefore, we must include them to not bias our data.

A portion of the funds are offered in various fund classes, but they have different fee structures. These show up as different funds in MSD, though fund size and excess return are identical. To prevent a single fund from being double counted, we use MSD's limitation of including only one share class for each fund. We choose funds share classes based on MSD's customizable priority lists. We prioritize the oldest share class, dependent on MSD's "Performance Start Date" variable, to ensure reportings of age are correct.

Our final notable limitation for the data set differs slightly from Pástor et al. (2015). They focus exclusively on the US market, which is significantly larger than the Nordic market, and the concentration of domestic and foreign investors is also quite different. While they only consider domestic funds within the US borders, we allow foreign funds that invest in the Nordic market. For precision, we deploy MSD's "Investment Area" metric over the conventional "Domicile", emphasizing our Nordic-centric focus. Here we chose Norway, Sweden, Denmark, Finland, Europe (North) and Scandinavia. Europe (North) and Scandinavia are used to include funds that don't specify their investment area to their respective country. The reason we're interested in including foreign funds investing in the Nordic market is not just because they make up a significant portion of the relatively small market, but also because they contribute to market efficiency by having an active position throughout the market. By not including foreign investors, we could potentially get an unclear view of the market's efficiency through industry size, which has an impact on the fund manager's ability to generate excess return (skill).

Both Dvořák (2005) and Shukla and van Inwegen (1995) provide evidence suggesting that investors tend to under-perform in foreign markets, much due to the information asymmetry. This could potentially lead to the foreign investors skewing the results, by performing worse than the Nordic investors. While this might be a justification to not include the foreign investors as a part of the Nordic market, we will keep them included. In TableA.2, we present the return to scale relationship on fund and industry level when excluding foreign investors. As seen, the interpretation of the results remain unchanged.

Capturing the size of an active industry is somewhat complicated. Most other articles, including Pástor et al. (2015) use domicile while excluding international funds. We argue this excludes foreign investors which will have an effect on the active markets. In addition, for our case it would have excluded for example a Norwegian fund investing in Sweden. This is captured by investment area, as we choose to use. Further, it would also have excluded funds whose investment area was Europe (North) or Scandinavia. Naturally these are also part of what we define as the Nordics. Europe (North) and Scandinavia combines to 185 funds that would have been lost. It is important to emphasize, especially when looking at the size of the active industry, that this does not include Nordic international funds. This makes the average industry size somewhat smaller than expected, but is necessary for our analysis as these can not plausibly be affected by the same forces as those who invest in the Nordics. It should however be noted that had we followed the standard “domicile approach”, our industry size would be even smaller.

4.2 Data cleaning and substitution

4.2.1 Fund size and excess return

We obtain 638 funds when we export the primary dataset from MSD based on the criteria discussed in section 4.1. Although, this current fund count is not the final total, as there are some data issues that require attention. Several monthly observations have missing values, and some funds aren’t reported at all for some key variables. We will now detail decisions to fill in these gaps and the exclusion of certain funds from the dataset.

Regarding observations on the fund size, 34 funds do not report their size. For excess return, 36 funds do not report. Furthermore, 30 funds do not report either of these values. We choose to exclude the funds that do not report any of their excess return or fund size, due to their lack of observations in other variables as well. Funds that miss only one of these two variables, we use substitutes or alternative methods to fill the gaps.

The 34 funds that do not report excess return can be explained by how this variable is calculated by MSD. Excess return is found by subtracting the fund's monthly return from MSD's own benchmark, which individually specify a fitting benchmark to each fund. The missing data occurs because MSD can not identify individual benchmarks for certain funds, and therefore returns the value N/A to our dataset. To fix this, we manually assign a suitable benchmark to these 34 funds based on their investment area and investment strategy. To avoid cherry-picking these benchmarks, we use similar benchmarks to what Morningstar Category Index has chosen for the comparable funds.

For the 36 funds that do not report fund size, we use the MSD defined variable "Total Market Value (Net)" as a substitute. We gather this variable from the fund's month-end net asset value. Comparing funds that are reporting both fund size and "Total Market Value (Net)", we find the values are nearly identical, with a maximum monthly difference of about 1-2%. Therefore, we consider this as a suitable replacement, allowing us to retain more funds in the dataset.

While reported values for fund size and excess return are now available, there are still instances of incomplete data owing to the inconsistency of monthly reporting across all funds. Specifically, for fund size, there are 145 funds with notable gaps in their reportings. A majority of these tends to report on a quarterly basis, whereas others do not show any clear patterns of reporting. On the other hand, excess returns are more consistently reported among the funds, with only two exhibiting gaps in their monthly reporting.

Since the fund size doesn't fluctuate much month-to-month, we use the Last Observation Carried Forward (LOCF) technique to impute missing values. This means if there's a gap in the fund size report, the most recent reported value will be carried forward until a new one is reported. Ignoring these gaps can lead to false variation between the observations, where some observations can go from reported to non-existing in a short time span, making the data skewed. In addition it would greatly bias our measure of industry size as we will see later.

When it comes to excess return, however, it can vary significantly from one month to the next. Consequently, we can't assume the excess return to be as consistent as fund size and can therefore not use the LOCF technique. This is the case for just two funds, therefore we leave their values for the affected months as N/A. By doing so, the regression models will automatically exclude the N/A's out of the regression where it will only focus on the funds where both fund size and excess return is reported.

After substituting and manually gathering data for fund size and excess return, we still have to remove another 25 funds due to missing reporting. However, we manage to retain a total of 45 funds for further analysis, meaning we end up with a total of 583 funds with complete reporting of excess return and fund size data.

4.2.2 Market capitalization

To access the total market capitalization in the Nordic market, we utilize the Bloomberg Terminal. From here, we export monthly data in USD currency from each country and then combine them with the main dataset gathered from MSD.

4.2.3 Eliminating other weaknesses

In finance, it's common practice to handle larger datasets by addressing extreme values using a process known as "winsorizing." We apply winsorization only to turnover rate, since we notice a skew in a small amount of the values within this variable.[9] The data will be winsorized at the 1st percentile in both the lower and upper tails to preserve as much data as possible and minimize unintentional biases, as mentioned by Adams et al. (2019). Instead of using the winsorizing technique to eliminate weaknesses for fund sizes,

[9] We have tried running most regressions which includes turnover ratio both with and without winsorizing. It does not change any conclusions.

we test different functional forms using the natural logarithm of fund size. This enables us to retain sizes that are atypical, but not unreasonable.

4.2.4 Potential biases in dataset

Incubation bias is a topic that has not been extensively studied within the Nordic fund market. As discussed by Evans (2010), incubation is a strategy that fund families might utilize when going public with a new fund. The approach involves launching multiple different funds privately. After evaluating their performance during their time being privately listed, the top-performing funds are selected for public disclosure. Evans' discovered that incubated funds outperform non-incubated ones by up to 3.5%, and they also attract a larger flow. However, this outperformance fades away post-incubation.

The lack of research (in contradiction to the US) could be because it simply isn't a bias threat in the Nordic market due to market regulations. After reaching out to The Norwegian Financial Supervisory Authority, Dassouli and Lund (2021) are told that regulatory practices constrain this practise. Since this information originates directly from them, we choose to trust the information.

4.3 Creating variables for analysis

Table 4.1 below summarizes the variables we utilize in the analysis based on given criteria and the data cleansing discussed earlier in sections 4.1 and 4.2. The variables are reported monthly in USD for easy comparability. The slight variation in observation in these variables arise due to the scarce reporting on active managed equity funds in specific areas within the Nordic region. For the upcoming analysis, we do not consider this as a problem, as the regression model will handle cases of nonsynchronous missing observations. Before discussing descriptive statistics, we list how each variable is created.

ExcessReturn is the fund's benchmark-adjusted gross return in percentage, where relevant benchmarks are chosen by MSD. Subtracting benchmarks from the funds provides a better insight into their performance independently, without market fluctuations or other forms of noise affecting their result. This allows us to use *ExcessReturn* as a performance variable in further analysis. *FundSize* represents the fund's total assets under management (AUM) for all share classes. To adjust for inflation, we divided by the total market capitalization of the corresponding month and then multiply this with the total stock market capitalization of December 2022. We divide *FundSize* by 10 million for easier readability.

FundAge is the fund's monthly cumulative age, starting from MSD's custom variable "Performance Start Date". The variable's first month is the fund's absolute first, meaning that any mergers are not counted as a new start or end. This gives us a view of the funds' actual experience throughout their fund's lifetime, but also ensures that merged funds with abnormal fund size or multiple years of knowledge are not considered as newly started funds. *IndustrySize* is the monthly total of all funds AUM divided by total market capitalization (sourced from Bloomberg Terminal) for the corresponding month, presented in percentage.

SmallCap is a dummy variable, with the variable equal to one if the fund trades small-capitalization stocks and 0 if not. The determination of whether the fund is small-cap or not is defined by MSD's variable StyleBox. We obtain this variable in a time-series with a unique value for each month should the fund change its strategy during its operations. *TurnoverRatio* measures the funds yearly trading activity in percent, defined by MSD's own variable as the lesser of purchases or sales divided by average yearly net assets.

SectorSize is the total AUM of all funds within a sector divided by the total market capitalization given that month. The variable is defined using MSD's 3x3 StyleBox, by the categories size (small-cap, mid-cap and large-cap) and investment style (value, blend and growth). *MgrExp* represents the cumulative months of experience the fund manager possesses within their respective fund, gathered from MSD variable "Manager History". *Risk* is the standard deviation of a fund's abnormal return for a 12 month rolling window, and defined by MSD as the residual of regressing excess gross return on the corresponding benchmark portfolio's return. Finally, we have the variable *FamilySize*, which is the sum of monthly *FundSize* within the same branding name. We divide this number by 10 million for readability.

Table 4.1: Summary statistics

				Percentiles				
Variable	Unique Observations	Mean	Standard Deviation	1st	25th	50th	75th	99th
ExcessReturn	57,706	0.009	2.211	-5.979	-1.092	0.004	1.074	6.260
FundSize	55,457	414.636	746.607	1.844	47.692	130.828	415.018	3,766.830
FundAge	117,981	140.685	104.435	3	55	121	207	430
IndustrySize	180	5.50	0.60	3.20	5.50	5.70	5.90	6.20
1(SmallCap)	44,518	0.205	0.404	0	0	0	0	1
TurnoverRatio	2,951	72.332	199.053	-27.515	20	42	80	513
SectorSize	106,120	1.20	0.80	0,02	0,60	1.10	1.90	3.60
MgrExp	80.668	51.981	50.754	1	16	37	73	226
Risk	74.768	2.333	1.272	0.5	1.349	2.044	3.123	5.766
FamilySize	103,500	4213.26	6184.73	0	76.620	929.100	5439.240	21,754.180

Table 4.1 reveals significant variation among different variables within the Nordic actively managed equity fund market. There is a notable difference in *ExcessReturn* that funds manage to achieve and their *FundSize* across various percentiles. Some of the variables also point to a wide array of investment strategies employed by the funds. Indicators such as *TurnoverRatio* and *Risk* hint at different approaches within the funds, where some seem to be taking an aggressive stance in their investment activities, while others seem to maintain a more passive strategy.

We suspect that certain countries in the overall average may skew the results in the variables in one direction. Therefore, we examine a more investment area specific summary of the variables in Table 4.2 below. For comparability, the specification of the variables will be calculated the same way as in Table 4.1.

Table 4.2: Summary statistics: investment area specific

	Mean					
Variable	Norway	Denmark	Sweden	Finland	Scandinavia	Europe (North)
ExcessReturn	0.031	-0.165	0.083	-0.093	0.1028	-0.004
FundSize	32.175	19.526	65.953	24.522	33.709	30.282
FundAge	196.392	157.180	169.793	171.023	182.823	143.237
IndustrySize	3.80	1.30	7.10	2.00	0.03	1.10
1(SmallCap)	0.169	0.078	0.234	0.253	0.088	0.233
TurnoverRatio	54.316	76.873	71.679	88.614	80.233	77.146
SectorSize	0.89	1.56	1.39	0.87	1.66	1.22
MgrExp	65.624	56.060	48.912	48.487	42.650	48.207
Risk	3.113	2.089	1.647	2.600	1.927	1.697
FamilySize	3488.799	2578.663	5706.75	4096.099	184.3794	3158.922

Table 4.2 highlights that some of the investment area specific variables stand out significantly compared to others. Denmark and Finland have a negative *ExcessReturn* compared to Norway and Sweden, meaning that on average during the period of 2008-2022 the funds have not managed to outperform their respective benchmark portfolio. Denmark and Finland also have a considerably lower *IndustrySize*, while Swedish funds have the largest size by far. Denmark continues to stand out from the other countries variables with a much lower share of *SmallCap*, while Norway stands out when it comes to *Risk*, being almost twice as large compared to Sweden's (3.113% vs. 1.647%).

Even though the investment areas *Scandinavia* and *Europe (North)* are important for getting a precise definition of the market, there is not much to discuss on their individual variables from Table 4.2. This is because it's hard to pinpoint the specific location within the Nordics where the funds are investing, complicating the interpretation. On the other hand, it is interesting seeing which direction the two investment areas are affecting the summary variables from the overall sample in Table 4.1. We see significant differences when specifying the statistic for each of the investment areas. However, it is important to bear in mind that there is also a considerable difference in the sample size for funds in the different areas, which could explain the variation in the variables. For example, *Scandinavia* only consists of 4 funds, while *Europe (North)* has 181 reported funds. These do not tell us much on their own, but are nevertheless a critical part of the overall study.

5 Analysis and discussion

We combine our analysis and discussion in this section. This means that the start will mostly be analytical with summary of potential biases, model specifications and other technicalities which must be considered. We then gradually move into more of a discussion about decreasing returns to scale, its determinants and skill.

5.1 Summary and bias of scale

In this section we will look at decreasing returns to scale using the methodology from Pástor et al. (2015) and Zhu (2017). Before adding control variables and concluding on hypothesis 1 and 2, we illustrate and discuss potential biases by showing both the OLS, OLS with FE and RD1 regressions. Recalling section 3, this means that the coefficients in column (3), (6) and (9) are found by eq.5 using the estimator from eq.9. For example, the coefficient for fund size under RD1 is found by regressing forward demeaned fund size, $\bar{q}_{it-1}$ on the backward demeaned fundsize, $\underline{q}_{it-1}$. Then we regress the fitted values from that regressing on the excess return. We lose two observations for each fund when using RD1. This is because we lose the first observation when backward demeaning (since there is no mean back in time to subtract) and we lose the second observation when forward demeaning (since there is no mean forward in time to subtract).

5.1.1 Fund size to performance relation

For *FundSize* our results are somewhat mixed. At the same time, significance and coefficients are somewhat as expected. Using OLS, we find the estimator to be both economically small and statistically insignificant. Before running the regression, *FundSize* is divided by 10 million. *ExcessReturn* is in units of percentage. This means that we can interpret the coefficient as: a 10 million dollar increase in *FundSize* is associated with a 0.0002% increase in *ExcessReturn*. This points in the opposite direction of our hypothesis. However, in accordance with section 3.3 the estimator is likely biased due to omitted variable bias and we do not infer any information from this other than to compare it with other methods.

Table 5.1: Summary of bias

The dependent variable in all regressions is *ExcessReturn*, which is the fund's benchmark-adjusted gross return. *FundSize* is the fund's total assets under management (AUM) for all share classes divided by total market capitalization, inflation adjusted and divided by 10 million. *IndustrySize* is the total of all funds' AUM divided by total market capitalization for the corresponding month, presented in percentage. Heteroskedasticity robust standard errors are shown in parentheses. All variables are monthly observations.

	Dependent variable: *ExcessReturn*								
Variable	OLS	FE	RD1	OLS	FE	RD1	OLS	FE	RD1
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FundSize	0.0002	-0.002	0.005				0.0002	-0.002	0.005
	(1.81)	(-5.35)	(1.31)				(2.48)	(-4.77)	(1.29)
IndustrySize				-0.083	-0.104	-0.084	-0.070	-0.077	-0.079
				(-5.07)	(-7.07)	(-4.95)	(-3.90)	(-4.97)	(-4.02)
Intercept	-0.003			0.465			0.388		
	(-0.32)			(5.02)			(3.76)		
Observations	52,815	52,815	51,649	57,030	57,030	56,457	52,815	52,815	51,649

When controlling for the unobservable skill we use fund fixed effects. By removing the omitted variable bias, our results are now statistically significant. The coefficient flips to become negative as our hypothesis expected. Further, it is somewhat more economically significant, with a 10 million dollar increase in fund size being associated with a 0.002% decrease in excess return. However, as discussed in section 3.4 this is also likely to be biased due to the finite sample bias which can produce a spurious regression. As we know this bias is likely to show decreasing returns to scale even where there are none. We can see that our RD estimator corrects for this. When running the regression using recursive demeaning, the coefficient is flipped once again to 0.005. Economically it is the strongest number produced for fund size, but it is no longer statistically significant with a t-value of 1.31.

We see the same pattern from the joint regression. Statistical significance only for fixed effects while OLS and RD remain insignificant. The coefficients are not identical, but similar enough to be rounded to the same numbers. Interestingly, statistical significance follows the same pattern as Pástor et al. (2015) from which our methodology is derived, where FE is statically significant while significance is lost when using RD. This causes the authors to question the power of the RD test, as "*a negative size-performance relation seems plausible a priori*" Pástor et al. (2015). Since our regressions show both statistical insignificance and a positive size-performance relation, this could cause us to question both the power and potential over-correction of the methodology. However, the finite sample bias would still be problematic when using FE and hence we cannot conclude using this regression. Further, the evidence from the Nordics is far more scant. This means that a negative size-performance relation cannot be seen as plausible a priori in our case. So far our evidence is in line with Pástor et al. (2015) and Phillips et al. (2018) of no decreasing returns to scale.

5.1.2 Industry size to performance relation

For *IndustrySize* we can tell a different story. Industry size is constructed in units of percentage, in the same way excess return is. Which means we are looking at the effects of a one percentage point increase in industry size. We should also cast our minds back to what industry size represents in our study before conducting this part. In this study it corresponds to the share of actively managed funds which invest in the Nordic area in percentage of the total market cap.

With this in mind we can observe that *IndustrySize* is both strongly significant and economically large using OLS. The coefficient is -0.083 and the corresponding t-statistic -5.07. In the joint specification the coefficient is -0.070 and the t-statistic -3.90. However as with fund size this method is likely to be biased due to cross-sectional differences in skill between funds. To correct for this, fixed effects are used. From table 5.1 we can observe that in both the individual and joint specifications, industry size is strongly statistically and economically significant. Running FE on only industry size we see that one percentage point increase in *IndustrySize* is associated with a 0.104% decrease in *ExcessReturn*. This is an economically large number, however when the average *IndustrySize* across our study is 5.5%, a 1% increase would be a rather large increase.

The RD regressions are also both statistically and economically significant in both cases. However, when running the RD regression on only industry size we are simply running the forward demeaned *IndustrySize* on the forward demeaned *ExcessReturn*. As noted in section 3.5 industry size is not likely to be biased in a fixed effects regression. Indeed both Zhu (2017) and Pástor et al. (2015) consider it an exogenous regressor. This means that under the specification with only *IndustrySize*, fixed effects are preferred. Recursive demeaning is only included for comparison. While under the joint specification (where fund size causes bias under FE) we look at RD. Either way, both specifications (5) and (9) are statistically significant and economically large. To summarize, the numbers of interest here are -0.104 with a t-statistic of 7.07 when only industry size is included. When we account for individual fund size the coefficient increases to -0.079 and is still highly significant with a t-statistic of -4.02.

What story does these numbers tell about Nordic markets? Pástor et al. (2015) find significant coefficients of -0.0326% under the FE specification including only *IndustrySize* and -0.0277% using the RD specification which included *FundSize*. This was in their main sample of 18 years (March 1993 - December 2011). The same relationship was found by Ferreira et al. (2015) for US funds, but the effects were observed to be weaker for non-US funds. Our findings support the idea of decreasing industry returns to scale. Put plainly, the results indicate that as the active market share increases, the ability of a single fund to outperform the market decreases. Contrary to Ferreira et al. (2012) however we observe that the effects are stronger in a non-US market. Before concluding on hypothesis 3 we add some controls to check for robustness. But first we end our methodological analysis by looking at the enhanced RD estimator from Zhu (2017).

5.1.3 Correcting for misspecifications using RD2

Finally, we look at the potential correction for misspecification using Zhu (2017). Here we present table 5.2 which looks at the RD2 estimator from equation 10. When *FundSize* is included, we now regress the forward demeaned lagged *FundSize*, $\bar{q}_{it-1}$ on the lagged *FundSize*, q_{it-1} and include the intercept in the first stage. We then regress the fitted values from this regression on *ExcessReturn*. Here we only lose one observation for each fund, as we do not use the backward-demeaned instrument. In the table below all specifications use the RD2 methodology.

Table 5.2: Correcting for misspecifications using RD2

The dependent variable in all regressions is *ExcessReturn*, which is the fund's benchmark-adjusted gross return. *FundSize* is the fund's total assets under management (AUM) for all share classes divided by total market capitalization, inflation adjusted and divided by 10 million. *IndustrySize* is the total of all funds' AUM divided by total market capitalization for the corresponding month, presented in percentage. Heteroskedasticity robust standard errors are shown in parentheses. All variables are monthly observations.

	Dependent variable: *ExcessReturn*		
Variable	(1)	(2)	(3)
Fund Size	-0.003		-0.003
	(-3.19)		(-3.08)
Industry Size		-0.084	-0.068
		(-4.95)	(-3.60)
Observations	52,232	56,457	52,232

As we can see from table 5.2 the estimators have flipped and become negative. Furthermore, in both the individual and joint specifications *FundSize* is now statistically significant, though it is economically small. A 10 million dollar increase in *FundSize* being associated with a 0.003% decrease in excess return. If it is not already evident from the literature and methodology section, model specification and choice of estimator is alpha omega in any model that includes fund size. This motivates our somewhat lengthy exploration of the topic.

The conclusion from this and more importantly our methodology section, must be that we abandon the RD1 estimator for the RD2 estimator. First, because Pástor et al. (2015) also question the power of RD1. Second, the reason for removing the intercept from the first-stage regression remains unjustified. Where Pástor et al. (2015) leaves us with questions, Zhu (2017) provides answers. In addition, we see from table 3.1, an increase in goodness of fit in the first stage which is almost identical in power to the increase found in Zhu (2017). This indicates the instrument fulfills the relevance condition better. From now on, we use the RD2 estimator where fund size is involved unless otherwise stated. Finally, we can now apply controls and conclude on hypothesis 1.

5.1.4 Controlling for within-fund variation over time

It is important that we are very precise about why we use the following controls, and not others. The methodology section should show that most factors affecting returns are already controlled for. By taking returns in excess of a benchmark we effectively control for risk, style, strategy and macro-factors affecting returns. Further, when recursively demeaning our variables we remove the cross-sectional variation. This leaves within-fund variation over time. We also know that in order for there to be an omitted variable bias, the omitted variable must be a determinant of the dependent variable and correlated with the independent variable of interest.

There is also a clear risk of introducing noise into our model. According to section 2.2.4, returns in excess of a benchmark should not be persistent as shown by Carhart (1997). The underlying assumption being that the stocks behind these returns follow a random walk so that once we account for risk, persistence is also random. When introducing a variable as a control we are effectively stating through omitted variable bias that the variable is a determinant of persistence (*ExcessReturn*). However, should the theory above hold and persistence is random, we run the risk of simply introducing noise into our model. Since a primary aspect of our theory is that scale has an effect on excess returns, it should be unproblematic to introduce variants of scale into our models. Other variables should be viewed with some skepticism. We further motivate this by looking to Pástor et al. (2015) and Zhu (2017) which conservatively apply controls one at a time. Our analysis will be a bit less conservative, but the potential of noise should be kept in mind throughout the analysis.

We use the RD2 estimator from the previous section and include a set of variables in table 5.3. All variables are lagged and forward demeaned when included in RD2. We instrument the forward demeaned fund size by using the lagged *FundSize*. The control variables chosen are: *FamilySize*, *SectorSize*, *TurnoverRatio*, *FundAge* [10] and *MgrExp*.[11]

[10]Morningstar Direct sometimes defines the start date of a fund after reportings of fund size, causing some loss of observations when including*FundAge*.

[11]We check for multicollinearity, over concern for the variants of size. However, both a correlation-matrix and VIF-test shows no signs multicollinearity.

Table 5.3: Controlling for within-fund variation over time

The dependent variable in all regressions is *ExcessReturn*, which is the fund's benchmark-adjusted gross return. *FundSize* is the fund's total assets under management (AUM) for all share classes divided by total market capitalization, inflation adjusted and divided by 10 million. *IndustrySize* is the total of all funds' AUM divided by total market capitalization for the corresponding month, presented in percentage. *FundAge* is the monthly cumulative fund age, the start being their first offer date. *FamilySize* is the sum of *FundSize* within the same fund branding name. *SectorSize* is the total AUM of all funds within a sector divided by the total market capitalization given that month, by the categories size (small-cap, mid-cap, and large-cap) and investment style (value, blend, and growth). *MgrExp* represents the cumulative months of experience the fund manager possesses within their respective fund. *TurnoverRatio* is the lesser of purchases or sales divided by the average monthly net assets. *Heteroskedasticity* robust standard errors are shown in parentheses. All variables are monthly observations.

	Dependent variable: *Forward Demeaned Lagged Fund Size*								
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FundSize	-0.003	-0.003	-0.003	-0.003	-0.003	-0.002	-0.001	-0.002	-0.002
	(-3.08)	(-3.12)	(-2.66)	(-3.04)	(-2.80)	(-1.80)	(-0.84)	(-2.17)	(-2.41)
IndustrySize	-0.068						0.009	-0.010	-0.009
	(-3.60)						(0.36)	(-0.45)	(-0.41)
FundAge		-0.001					-0.001	-0.001	-0.001
		(-4.88)					(-4.35)	(-4.50)	(-4.89)
FamilySize			-0.0002				-0.0004	-0.0003	-0.0003
			(-3.62)				(-4.23)	(-3.99)	(-4.03)
SectorSize				-0.189			-0.241	-0.092	-0.093
				(-2.91)			(-2.86)	(-1.35)	(-1.37)
MgrExp					-0.001		-0.0002	-0.0003	
					(-2.59)		(-0.76)	(-1.12)	
TurnoverRatio						0.001	0.001		
						(3.55)	(2.65)		
Observations	52,232	51,828	52,265	52,265	51,700	31,225	30,637	51,263	51,828
R^2	0.05%	0.1%	0.03%	0.03%	0.02%	0.1%	0.3%	0.1%	0.1%
F Statistic	11.927***	14.433***	7.726***	7.306***	5.711***	14.527***	11.081***	8.316***	9.821***

Before analyzing the coefficients we note that r-squared is very low in nearly all regressions. This is a recurring theme for our regressions and indicates a poor model fit. Two things should be noted as to why this might not be a critical issue. First, this seems to be common in the literature. Both Zhu (2017) and Pástor et al. (2015) do not report r-squared in their studies.[12] The only study we could find which uses our methodology on scale and reports r-squared is Adams et al. (2019). Their results are comparable to ours. Both when using FE and RD, r-squared is very low. It should be noted that the study is generally critical to Pástor et al. (2015), but not because of the methodology producing a low r-squared. The second reason is because of the discussion above. We are trying to measure an effect on excess return, which in theory should not be possible. Here, even a low explanatory power of the variation in excess return can yield valuable information.

[12]Zhu (2017) does discuss r-sqaured but only in the context of the first-stage regression to show the relevance of the instrument.

Table 5.3 also shows that *FundSize* is robust in nearly all specifications except those which include *TurnoverRatio*. Two things should be noted about the inclusion of *TurnoverRatio* however. First, following the discussion above, *TurnoverRatio* can easily introduce noise in our regression. Second, the reporting of the variable in MSD had inconsistent reporting. The gaps in data caused by this could not be confidently filled in the way *FundSize* was, causing us to lose nearly 40% of our observations when including this variable. Given these two issues we can not confidently reject the hypothesis in specifications that include *TurnoverRatio*.

We also observe that *FundAge* enters statistically significant with a negative coefficient. This indicates that funds have decreasing returns over their lifetime even when controlling for the effects of scale. In addition, *MgrExp* also has a negative effect on returns, even when controlling for scale. This is consistent with Pástor et al. (2015) which finds newer managers to be more skilled than older ones. However, the significance is lost when adding additional controls.

FundSize is found to be robust for all forms of size, including *FamilySize*, *SectorSize* and *IndustrySize* jointly. There is also evidence that the size of the funds family matters, though the number is economically weak at -0.0003% for a 10 million dollar increase in the size of the family. However, it should be noted that the size of the family is usually far larger than the size of a single fund. Our descriptive statistics show a mean family size of 4.2 billion, which shows it is not as weak economically as the number suggests. What could potentially explain this? It is possible the solution lies in liquidity constraints as Berk and Green (2004) describes. Especially if funds in the same family have the same manager, who considers the same shares in the market for different funds in the same family. Alternatively if the employees of the firm work for more than one fund in the same family.

SectorSize also enters statistically significant, though significance is lost in the joint specifications. The coefficients seem economically strong until we consider that the average sector size is 1,2% wherein a 1% increase would mean almost a doubling in the size of the sector.[13] While statistically insignificant, we are careful to rule out its effect here. Much like *IndustrySize*, the controls in this section likely introduce noise when looking at *SectorSize*. For example is a single funds turnover an omitted variable which can be thought to have a correlation to sector size? In addition, should it be a determinant of excess return? Should the question to either of these questions be no, including it likely introduces noise to the model. It should again be noted that both Pástor et al. (2015) and Zhu (2017) consider endogeneity not to be a problem for industry size. Given the similarity between the variables it is not a far stretch to apply this logic to sector size as well. We will consider *IndustrySize* and *SectorSize* more carefully in the next section. The conclusion from this section is that we can confirm hypothesis 1, as it remains robust in all specifications not plagued by large observation losses:

1. *Nordic funds show decreasing returns to scale at the fund level.*

We follow Pástor et al. (2015) and Zhu (2017) in assuming linearity for *FundSize*. However, we also test log(*FundSize*) in the specification from column (8). Doing this we obtain statistically significant and economically stronger numbers. This could indicate a non-linear relationship and influence from extreme values. We also provide evidence for the latter point by splitting funds into quintiles based on average size. The regression shows that diseconomies of scale are more pronounced for quintiles 2-4, while quintile 1 is not significant and 5 shows positive coefficients. This could indicate thresholds where *FundSize* matters. For example smaller funds might not have a large price impact, and that at a certain size, funds have adapted their strategies to avoid diseconomies of scale. We show these results in the appendix: A.4, A.3. Next, we take a closer look at industry size before concluding on hypothesis 2.

5.1.5 A critical look at industry return to scale

To determine whether there is industry return to scale for actively managed funds in the Nordics, we must take a closer look at *IndustrySize* while controlling for other components

[13]Keep in mind we are not talking about a percentage increase as with for example log. We are talking about a unit increase of 1, which in this case corresponds to a 1 percentage increase. This has the same interpretation as *IndustrySize*.

that may influence its results. As mentioned under 5.1.4, Pástor et al. (2015) and Zhu (2017) do not consider endogeneity to be a problem for the *IndustrySize*. Thus, we will be careful when introducing new components to *IndustrySize* and potential noise to our results when doing our regressions.

Dissimilar to Pástor et al. (2015), we do not encounter any clear trend of *IndustrySize* in the nordics. Rather, the variable seems to increase in the start before it eventually flatten out. For that reason, we consider a time-trend unnecessary in our case. However, when looking at appendix A.2 of how *IndustrySize* has developed during the time-series, we see that *IndustrySize* fluctuated an abnormal amount in 2008. A logical explanation to this is that we are seeing the effects of the financial crisis. During the time span of our dataset we also have the effects of the pandemic in 2020. Even though the *IndustrySize* of 2020 doesn't have as dramatic fluctuations as 2008, there could still be abnormal effects on *ExcessReturn*. Therefore, we are adding two dummy variables of the year 2008 and 2020 to control for this.[14]

We also include the average *FundSize* and the number of funds operating in the market each month. Jointly these make up *IndustrySize*. Doing this allows us to see if both components contribute to the negative coefficient in *IndustrySize*. The last component we will control against the *IndustrySize* is *SectorSize*. Here we will take a closer look at the relationships between the competition within the sectors funds are investing in and their industry scale of return. We summarize the findings in table 5.4 below. Since *FundSize* is not included, all regressions are estimated using OLS with FE.

[14] Again, we check for multicollinearity. Both a correlation-matrix and VIF-test shows no signs multicollinearity.

Table 5.4: A critical look at industry return to scale

The dependent variable in all regressions is *ExcessReturn*, which is the fund's benchmark-adjusted gross return. *IndustrySize* is the total of all funds' assets under management (AUM) divided by total market capitalization for the corresponding month, presented in percentage. *Dummy2008* is a dummy-variable which equals zero if the date of fund-observation equals to year 2008, and one otherwise. *Dummy2020* is a dummy-variable which equals zero if the date of fund-observation equals to year 2020, and one otherwise. *AvgFundSize* is the average fund's total AUM for all share classes divided by total market capitalization, inflation adjusted and divided by 10 million. *NFunds* is the total volume of active operating funds. *SectorSize* is the total AUM of all funds within a sector divided by the total market capitalization given that month, by the categories size (small-cap, mid-cap, and large-cap) and investment style (value, blend, and growth). Heteroskedasticity robust standard errors are shown in parentheses. All variables are monthly observations.

	Dependent variable: *ExcessReturn*									
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
IndustrySize	-0.104	-0.153	-0.095	-0.106	-0.136	-0.082	-0.123	-0.140	-0.133	-0.100
	(-7.07)	(-4.39)	(-6.42)	(-5.26)	(-9.04)	(-4.41)	(-2.57)	(-2.96)	(-3.33)	(-4.60)
Dummy2008		0.157					0.116	0.112	0.125	
		(-3.10)					(0.97)	(0.93)	(1.10)	
Dummy2020			-0.479				-0.398	-0.396	-0.398	
			(-8.41)				(-6.96)	(-6.95)	(-6.93)	
AvgFundSize				0.001			-0.002	-0.004		-0.005
				(0.12)			(-0.48)	(-0.82)		(-1.01)
NFunds					-0.006		-0.004	-0.004	-0.004	-0.006
					(-9.81)		(-6.86)	(-6.98)	(-6.93)	(-9.60)
SectorSize						-0.183	-0.217		-0.222	-0.187
						(-2.31)	(-2.47)		(-2.64)	(-2.19)
Observations	57,027	57,027	57,027	57,027	57,027	57,027	57,027	57,027	57,027	57,027

As shown in Table 5.4, *IndustrySize* is economically and statistically significant when regressed on its own, with a coefficient of -0.104 and t-statistic of -7.07 in column (1). This can be interpreted as when *IndustrySize* increases with 1%, the *ExcessReturn* decreases with 0.104%. When introducing additional factors into the regression, we observe that *IndustrySize* continues to remain statistically and economically significant for all spesifications, with coefficients consistently displaying a negative sign. This suggests evidence supporting the existence of a decreasing return to scale relationship for *IndustrySize*.

When including *NFunds*, we observe that the estimator has a negative coefficient. This result can be interpreted as an increase in the number of active funds in the markets leads to a decreasing return to scale. This makes sense, as with more funds actively moving capital in the market, there would be more price corrections within the investments positions, making the excess return harder to create. It is also conceivable that as more funds compete for mispriced securities, it becomes more challenging for fund managers to find them.

More surprisingly, we find that *AvgFundSize* has a positive coefficient sign, thereby indicating an increasing return to scale. However, the coefficient itself is not significant, and we also see evidence the coefficient shifting back to a negative sign in the joint regression. The coefficient for *SectorSize* in the joint regression is also negative, which indicates that there isn't good evidence for a relationship. For *SectorSize*, the coefficient is statistically significantly and negative, indicating that an increasing *SectorSize* has a negative relationship with *ExcessReturn*. In other words, increased competition (more funds) within the same sector indicates a lower excess return. The evidence is in line with Hoberg et al. (2017) and can also makes sense intuitively. We can think of an increase in industry size analogous to an increase in competition, as more funds push prices towards market efficiency. It then makes sense that an increase within the funds sector, which consists of funds trading similar (or the same) securities, the competitive effect would be bigger. This is also what we see, as the economical effect is nearly twice that of *IndustrySize*.

The outcomes of the joint regression (7), mostly align with the findings obtained from individual regressions conducted with one estimator at a time. As already mentioned, *AvgFundSize* becomes negative, but the coefficient loses its significance. The dummy-variable *Dummy2008* also loses its significance, and therefore can provide enough evidence to explain its influence. Other than that, *IndustrySize* keeps its significance with a negative value throughout all of the regressions done. We also find additional interesting findings in the course of the process that will eventually be further discussed. As *IndustrySize* is robust in all specifications, we can therefore confirm hypothesis 2:

2. *Nordic funds show decreasing returns to scale at the industry level.*

5.2 A closer look at each sampled country

So far, we have considered the Nordic market without specifically isolating each of the countries combining it. We now aim to present a more descriptive picture of how the different countries in the market are structured. This should help us understand *FundSize* and *IndustrySize* more clearly and allows us to decide whether or not to confirm hypothesis 3 and 4. Since we define the Nordic market as a combination of several individual countries, it is possible that one or more countries may skew the results in a certain direction. Looking at each country's individual values gives us a clearer insight into whether the countries share enough characteristics to define themselves as a large Nordic market together and whether, generally, they experience the same effects of scale.

An important point to keep in mind in the upcoming analysis is that we lose about 20 percent of the observations by defining *FundSize* and *IndustrySize* for each country. This is because many of the Nordic observations investment areas are defined as "Europe North" and "Scandinavia" rather than a specific country name, consequently leading to an exclusion. Another point is that there is also a significant difference in the numbers of funds observed in the different countries, meaning we have to be critical when analyzing the regressions results individually.

Presented in Table 5.5 are *FundSize* and *IndustrySize* regressed on *ExcessReturn* for each country sampled. Following the methodology section, every regression which includes *FundSize* is estimated using RD2, while those with *IndustrySize* using FE. In both of the methods all independent variables are lagged. When applying RD2, variables are also forward-demeaned, while we instrument for forward-demeaned *FundSize* using lagged *FundSize*.

Table 5.5: *FundSize* and *IndustrySize* for each sampled country

The dependent variable in all regressions is *ExcessReturn*, which is the fund's benchmark-adjusted gross return. *IndustrySize* (shortened to "*Ind*" in tables variable list) is the monthly total of all funds assets under management (AUM) divided by the total market capitalization for the corresponding month. *FundSize* (shortened to "*Fund*" in the tables variable list) represents the fund's total AUM divided by the total market capitalization. *FundSize* is the fund's total assets under management for all share classes divided by total market capitalization, inflation adjusted and divided by 10 million. Heteroskedasticity robust standard errors are shown in parentheses. All variables are monthly observations.

	Dependent variable: *ExcessReturn*							
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ind_Denmark	0.004 (3.26)							
Ind_Norway		-0.262 (-6.32)						
Ind_Sweden			-0.267 (-8.91)					
Ind_Finland				-0.415 (-7.09)				
Fund_Denmark					-0.061 (-5.79)			
Fund_Norway						-0.018 (-4.15)		
Fund_Sweden							0.001 (1.22)	
Fund_Finland								-0.005 (-0.75)
Observations	5,745	9,505	20,065	5,525	5,688	9,425	19,860	5,476
R^2	0.2%	0.4%	0.4%	0.9%	1.1%	0.004%	0.0119%	0.03%
F Statistic	10.648***	39.991***	79.429***	50.302***	64.339***	0.455	2.364	1.897

The results from Table 5.5 above show that all countries have a significant effect from *IndustrySize*. For Norway, Sweden, and Finland, the coefficients are negative, indicating decreasing return to scale. On the other hand, Denmark's relatively low coefficient is positive, suggesting increasing return to scale relationship. However, Denmark suffers from a small number of fund-month observations compared to the others, causing uncertainty about concluding anything further with this result. We also see a very high coefficient of -0.415. This might seem arbitrarily high, but given the small size of the industry it might be a economical effect.

FundSize, shows more varied results between the countries. The coefficients are statistically significant for Denmark and Norway, where we also see decreasing return to scale. For Sweden and Finland, the coefficients are not significant, with Sweden showing increasing returns to scale. The results from the RD estimates align well with the findings from

Table A.3 in the appendix, where we present the size-performance relation for different quintiles based on size. For the 5th quintile, it is shown that the funds with the largest *FundSize* indicates increasing return to scale relationship. Equivalently Sweden is also by far the leading country in average *FundSize*. This may indicate that Swedish fund managers adjust their strategies favorably when they exceed a certain size. For instance, change their strategy to mid-cap and large-cap where liquidity is less of a concern.[15] This could be the reason for the results of going from decreasing return to scale to increasing return to scale.

The result for Finland in column (8) is more ambiguous. Since there are a significantly smaller portion of observation in this country we need to be more careful when discussing the results. The coefficient is negative, but is not statistically significant, meaning we don't have enough evidence to conclude Finland's return to scale relationship. We can once again compare this to the quintile regression. The 1.st quintile shows that the funds with the smallest size do not have a significant coefficient when explaining the return to scale relationship, which is the same results as when looking at Finland individually. Equivalently, average *FundSize* is also significantly smaller in Finland (245 million) compared to Norway and Sweden (321 million and 659 million).[16] A possible explanation might therefore be a higher concentration of smaller funds in Finland, which does not have a significant price impact once size increases.

The fact that countries behave differently in comparison to each other opens the door to a discussion on how we define the Nordics, especially in terms of *IndustrySize*. For *FundSize*, taking the Nordics as a whole mostly allows us to work with a much larger sample size. We can effectively consider the countries jointly as the Nordics and individually. For *IndustrySize* this might be more problematic. Since the number is calculated as the sum of AUM for all funds divided by the sum of the market capitalization for all the countries. This could potentially introduce some bias. For example, will a firm with investment area Denmark be affected by an increase in the size of funds investing in Norway? Perhaps

[15]As presented in Figure A.7 and Figure A.8, we can see the funds in the 5th quintile invest a smaller amount in small-cap than funds in the 1st quintile.

[16]Denmark however has an even lower average *FundSize* and yet shows decreasing returns to scale. So perhaps this is not the full explanation.

the size of countries' industries should be considered individually as above. On the other hand, this would exclude investment areas such as Scandinavia and Europe (North).

This leads to an even larger discussion of how *IndustrySize* is calculated in both Pástor et al. (2015) and Zhu (2017). Their calculation of *IndustrySize* is more straightforward as it entails only the US. However, what about for example a global fund investing partly in the US? Surely this is active capital not included in their analysis. Perhaps using an active share of all active investments is the right answer. On the other hand, such measures often include for example hedge funds which are not part of the mutual fund industry. The conclusion from this discussion should be to highlight that *IndustrySize* is difficult to measure precisely, and that there is no right answer in this regard. However, we stick with our original definition while pointing out potential problems with the definition of the variable. In addition, with most countries showing decreasing returns to scale at the industry level individually, this indicates the variable might be fitting afterall.

After examining the individual countries' *FundSize* and *IndustrySize*, we can conclude that the countries are more similar than dissimilar. Nevertheless there are differences between the countries, which means we can reject hypotheses 3 and 4:

3. *When looking at each sampled country in the mainland Nordic region, each country exhibits decreasing returns to scale at the fund level.*

4. *When looking at each sampled country in the mainland Nordic region, each country exhibits decreasing returns to scale at the industry level.*

5.3 The determinants of the size-performance relation

Having shown decreasing returns to scale both on the fund and industry level in the Nordics, we now turn our attention to the determinants. This section tests if small-cap trading funds and funds with a high turnover ratio are more prone to the effects of decreasing returns to scale due to price impact, as predicted by Berk and Green (2004). If we recall the literature section, this means that we are testing hypotheses 5 and 6. We also include a risk measure since funds with higher risk are more likely to have a larger active share in its portfolio. Because they have a larger active portfolio we once again expect such firms to have larger trading cost and price impact once scale increases. We therefore use the variables *1(SmallCap)*, *TurnoverRatio* and *Risk*.

To achieve this we look at each variable's interaction with *FundSize* and *IndustrySize* in the table 5.6. When a coefficient enters negative and significant we can state that the variable is associated with steeper decreasing returns to scale. Since the interaction term soaks up some of the effect from the original variable (*FundSize* or *IndustrySize*) it does not matter if the original variable enters insignificant or with weakened economical interpretation. The findings are summarized in the table below. Following the methodology section, every regression which includes *FundSize* is estimated using RD2, while those without use FE estimated by OLS. All variables are lagged and when RD2 is used the variables are also forward-demeaned, while we instrument for forward-demeaned *FundSize* using lagged *FundSize*.

From the table above we observe that the determinants of *FundSize* are as expected in the Nordics. When a fund is classified as small-cap it is indeed more prone to the effects of scale. We see that the coefficient is negative and significant in all specifications. The same is also the case when a fund has a higher *TurnoverRatio*. Jointly these provide evidence for the theory of liquidity constraints from Berk and Green (2004). As the scale of these funds increases, the managers must now find new ways to generate the same return at a larger scale. Either, they must now spread their skills to find several new stocks which would mean spreading their skill too thin, or they must trade larger quantities of the same stocks, but with a larger price impact. The observation is also confirmed by *Risk*, which enters negative and significant in all specifications.

The overall conclusion on fund size from Table 5.6 should be that the liquidity of the firm's asset or the assets it wants to attain determines the effect experienced from a growing fund size. We note that we find evidence of this using the enhanced RD2 estimator in the Nordic markets, while Pástor et al. (2015) could not find this using the regular RD estimator in the US. At the same time, missing observations should be mentioned. As mentioned previously, we lose a substantial amount of observations due to missing reports

Table 5.6: Determinants of the size-performance relation

The dependent variable in all regressions is *ExcessReturn*, which is the fund's benchmark-adjusted gross return. *FundSize* is the fund's total assets under management (AUM) for all share classes divided by total market capitalization, inflation adjusted and divided by 10 million. *1(SmallCap)* is a dummy-variable equal to one if the fund is trading small-cap stocks, and zero otherwise. *TurnoverRatio* is the lesser of purchases or sales divided by the average monthly net assets. *Risk* is residual of regressing excess gross return on the corresponding benchmark portfolio's return, for a 12-month rolling window. *IndustrySize* is the total of all funds' AUM divided by total market capitalization for the corresponding month, presented in percentage. *FundAge* is the monthly cumulative fund age, the start being their first offer date. Heteroskedasticity robust standard errors are shown in parentheses. All variables are monthly observations.

	Dependent variable: *ExcessReturn*							
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FundSize	-0.001	-0.001	-0.004				0.001	0.001
	(-0.91)	(-0.86)	(-2.69)				(0.26)	(0.31)
*FundSize*1(SmallCap)*	-0.016						-0.014	-0.014
	(-3.75)						(-2.78)	(-2.77)
*FundSize*TurnoverRatio*		-0.0002					-0.0001	-0.0001
		(-3.15)					(-2.39)	(-2.45)
*FundSize*Risk*			-0.009				-0.009	-0.008
			(-3.69)				(-2.32)	(-2.17)
IndustrySize				-0.093	-0.124	-0.108	-0.095	-0.071
				(-4.84)	(-6.77)	(-7.16)	(-3.64)	(-2.51)
*IndustrySize*1(SmallCap)*				-0.016			0.119	0.114
				(-1.65)			(1.80)	(1.73)
*IndustrySize*TurnoverRatio*					0.0002		-0.0005	-0.0004
					(4.34)		(-1.46)	(-1.35)
*IndustrySize*Risk*						0.018	0.059	0.060
						(6.66)	(-2.42)	(-2.45)
FundAge								-0.001
								(-2.24)
Observations	40,786	31,225	48,912	42,250	33,387	53,388	25,005	24,840
R^2	0.05%	0.04%	0.04%	0.1%	0.2%	0.2%	0.2%	0.2%
F Statistic	10.104***	6.029***	8.718***	13.768***	32.973***	46.619***	5.322***	5.316***

of turnover ratio. Unfortunately, we also lose some observations with the small-cap dummy. Whilst acknowledging this we can confirm hypothesis 5:

5. *The determinants of decreasing returns to scale at the fund level are consistent with the theory of liquidity constraints from Berk and Green (2004). This implies funds with a higher turnover ratio and which have a strategic focus on small-cap stocks exhibit steeper decreasing returns to scale at the fund level.*

While the determinants of fund size are as expected, the determinants of industry size are not. The results are a mixture of either not significant or showing less steep decreasing returns to scale with the interaction variables. Given this, we find no evidence for the mechanics behind industry decreasing returns to scale in the Nordics. This gives rise to two questions. First, if these interactions explain industry decreasing returns to scale in the US as shown by Pástor et al. (2015), why is this not the case for the Nordics? Second, if these interactions do not explain the mechanics behind industry decreasing returns to scale, what does? In the subsequent paragraphs we allow ourselves to speculate on these questions.

One possible explanation might lie in different levels of liquidity between US and Nordic markets. As shown by Jain (2003), liquidity in US markets (especially NASDAQ and NYSE) is higher than most other countries in the world, including the countries which make up the Nordic market. Given a lower general liquidity in the market it might be the case that an increase in *IndustrySize* would impact prices of large and mid-cap stocks similar to that of small-cap stocks. This could explain why we find no statistically significant difference. However, if this is the case, should not the same be observed by an increase in *FundSize*? Contrary to this, even with an increase in size, a single fund is unlikely to have a price impact on a large-cap stock. On the other hand, if liquidity is low in the Nordics for large/mid-cap stocks as well, then an increase in industry size could push prices so that no single firm can exploit mispricing opportunities. Obviously this would be much the same mechanic as with small-cap stocks in the US.

While the paragraph above might explain why the small-cap dummy interaction is not significant, should not a higher turnover ratio still cause steeper decreasing returns to scale by picking up both the effect from large and small-cap stocks? We do see indications of this in the joint specifications, columns (7) and (8), however, the results are not significant. Scant reporting and issues with model specifications should also be mentioned as possible explanations. Indeed we see some coefficients change from negative to positive or vice-versa between the FE (only *IndustrySize*) and RD2 (*FundSize* included) specifications which seems unlikely. This can also be related to the wider discussion of how *IndustrySize* is defined in our study. We therefore test for each country individually. The results are once again not significant or show positive interactions. As an example we show the results from Norway in appendix A.1.

To summarize, the determinants of industry size in the Nordics may differ because the Nordics are indeed different, or because of limitations from our model specifications. Either way, we find no evidence of the mechanics behind industry decreasing returns to scale. This means we reject hypothesis 6:

6. *The determinants of decreasing returns to scale at the industry level are consistent with the theory of liquidity constraints from Berk and Green (2004). This implies funds with a higher turnover ratio and which have a strategic focus on small-cap stocks exhibit steeper decreasing returns to scale at the industry level.*

5.4 Skill

As discussed previously, unobserved skill from the cross section is problematic for our regression models. If there is indeed a difference in skill between funds, it gives rise to omitted variable bias. The literature on this varies. However, as discussed there are likely unexploited mispricing opportunities. The possibility of exploiting these however disappears as the size of the fund and surrounding industry increases. With our model we can analyze skill on a fund-level by effectively removing the effect from *FundSize* and *IndustrySize*. To achieve this we begin with the fund fixed-effects model and expand it to include the interactions from table 5.6, column (7). This means we use eq.12 where x includes *FundSize*, *IndustrySize* and their interactions with *TurnoverRatio*, *1(SmallCap)* and *Risk*.

12. $R_{it} = a_i + \beta x_{it-1} + \epsilon_{it}$

Using this model we observe fund fixed effects, a_i which can be interpreted as the funds alpha. This equals R_{it} when $x_{it-1} = 0$. In other words, we observe *ExcessReturn* without the effects of *FundSize* and *IndustrySize* and their interactions with *TurnoverRatio*, *1(SmallCap)* and *Risk*. While skill is assumed to be constant over time (we obtain only one value of a_i for each fund), it is calculated using each fund's full time-series. We then simply take the average from the cross-section and can plot skill over time as differently-skilled funds enter and exit our panel. We show the results from this in figure 5.1, Graph A and Graph B. We then estimate eq.12 again, but this time we include *FundAge*, analogous to column (8) from table 5.6. This time we extract a_i and the coefficient from *FundAge*, $\hat{\beta}_{age}$. With both these tools we now allow skill to vary over time for each fund using equation 13. We show these results in figure 5.2, Graph C and Graph D.

We acknowledge that the Fund fixed effects is not a perfect representation of skill, but rather a theoretical one. The fund fixed effects actually picks up everything unique to the fund, including skill. However we assume our benchmarks are properly applied so we control for strategy and risk.[17] When assuming this, the model of Pástor et al. (2015), based on Berk and Green (2004) assumes only scale can have an effect on the excess return - so that once we control for this, alpha coincides with "true skill" from the Berk and Green model. While it is not perfect, going forward, this is what we mean by "skill".

13. $Skill_{it} = a_i + \hat{\beta}_{age-it} * FundAge_{it} + \epsilon_{it}$

[17] Should funds take risks in ways the benchmark does not pick up, this could make the fund fixed effects pick up the excess risk, rather than their skill.

Figure 5.1: Constant skill over time

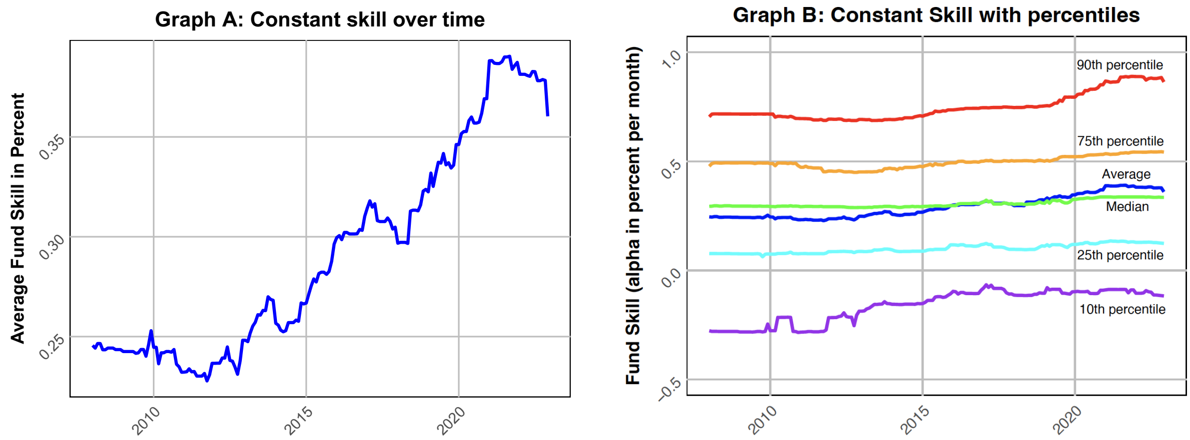
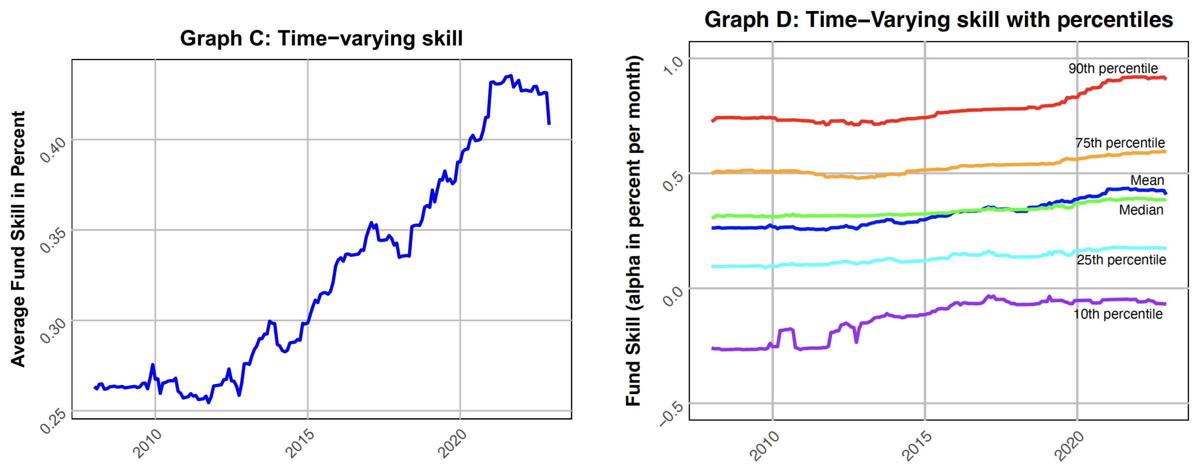
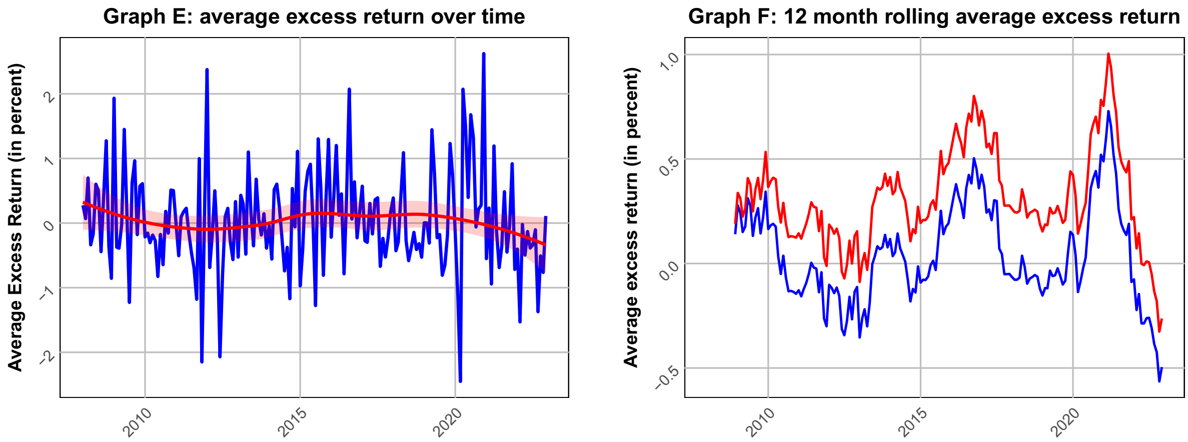


Figure 5.2: Time-varying skill



From the graphs above we can make several points. First, skill shows a clear upwards trend both when constant over time and not. We see that with constant skill, excess return in absence of scale increase from about 0.25% to about 0.36% This is in line with what Pástor et al. (2015) find for US markets. When skill is constant over time, Graph A and B implies that new funds on average are more skilled than the funds which exit the panel. Thereby increasing overall skill in the market. Second, from Graph C and D it is also implied that funds have an increase in skill over time, which we already know since $\hat{\beta}_{age} = 0.0002 > 0$. However, comparing Graph A and C, the effect of increased skill over time is far lower than the effect from the more skilled entries in our dataset. Even at the end of 2022, this only accounts for about a 0.05% difference between time-varying and constant skill. Finally, the increase in skill mostly arises from the most skilled funds

Figure 5.3: Excess return



(90th percentile) and least skilled funds (10th). This could indicate that the least skilled funds have exited the markets, and have been replaced by more skilled firms, since the effect from time-varying skill is relatively low. In conclusion, we can confirm hypothesis 7:

7. *Nordic funds show increasing skill over time when controlling for the effects of scale.*

Despite the increase in skill however, we observe from figure 5.3, Graph E that funds at the end of our study actually underperform compared to funds at the beginning of our study. In other words, the increase in skill has not translated into an increase in *ExcessReturn*. This is also what Pástor et al. (2015) find in US markets. The reason for this should be evident given earlier sections of our analysis: the effects of scale, and its inverse relationship with performance. In short, Nordic funds have become more skilled over time, but due to an increase in the size of the industry and individual fund size this has failed to translate into increased performance. For robustness we also plot skill excluding turnover ratio as a determinant given the earlier discussion about missing observations. The graph also shows an upward trend and can be found in appendix A.6.

Pástor et al. (2015) concludes that the increase in industry size over their time-series explains how skill increases while excess return does not in their study. For the Nordics, this can not be the only explanation as IndustrySize only increases at the start of our time-series before flattening out as shown in appendix A.2. We also show this in figure 5.3, Graph F, which plots *ExcessReturn* on a 12 month moving average, along with *ExcessReturn* adjusted for *IndustrySize*. To adjust for *IndustrySize* we run eq.12 but include only *IndustrySize* on the right hand side. We then take the coefficient from this regression (-0.104) and multiply it with ($IndustrySize_t$-$IndustrySize_0$). This gives us *ExcessReturn* had *IndustrySize* stayed at the same level as in 2008. Graph F shows that the increase in *IndustrySize* certainly explains some of the skill in the industry, since managers in absence of competition produce a higher excess return. However it does not exhibit an obvious upwards trend as industry size does not increase over our time-series. This means we must consider additional explanations.

Another explanation might lie in an increase of the average fund size, and a decrease in the number of funds over (most) of the period. Before explaining this, we must connect it to the overall literature. In section 2.2.5 we highlight two rather contradictory stories in the overall literature. First, there are likely mispriced securities in the markets (as markets are not fully efficient). Second, mutual fund returns are unlikely to stay persistent over time. Assuming mutual fund investors are indeed professionals who are more skilled than the average investors, how can these two facts coincide? Again, the answer is the size-performance relation.

Imagine a fund which employs a manager who is more skilled than other managers in the industry. The manager can find and invest in mispriced securities as amongst others Bondt and Thaler (1985) predicts. We now introduce the investors from Berk and Green (2004) who can observe this skill (though importantly not perfectly) and increase the flow to the fund. Through price impact and spreading skill too thin however, the increase in size has an adverse impact on performance - and so the fund will not show persistence over time. In essence, investors of mutual funds create an efficient fund market the same way investors in stocks create efficient stock markets. They move between funds based on their perception of skill so that funds are the "correct size" based on their skill.[18] Our study empirically supports this story for the Nordics. We achieve this by showing fund

[18]This implies some funds might be inefficiently sized. Meaning they do not have the correct amount of capital given their skill.

decreasing returns to scale, its determinants and an increase in skill over time which does not lead to persistence of excess return.[19]

The paragraph above may explain how the skill of a single fund will not contribute to persistence. For it to explain how the industry on average shows increased skill and yet no increase in excess return, it would require that the funds in the industry on average become larger. In appendix A.3, we show an upward trend in fund size, and a downward trend in the number of funds. The average fund becomes larger, and there are less funds in the market, which then roughly keeps industry size constant. With fewer and more skilled funds, investors then cancel out their increased skill by moving to these funds increasing the average size.

Finally, we may note that average fund size does not increase over the whole time-series.[20] Therefore a final explanation might be an increase in the number of small-cap investing funds. As explained earlier, this is where skill is most likely to be picked up as this is where mispricing opportunities are most likely to occur. In appendix A.5 we show an increase in small-cap investors over the whole time-series. To conclude, the increase in skill not leading to an increase in *ExcessReturn* in the Nordics is likely explained by an increase in average fund size, industry size and small-cap investors over the time-series.

[19]We may also note articles such as Järf (2016) which finds evidence of persistence in the Nordics. Our findings still makes sense in this context. Since the persistence over time is eroded by increased flows from investors slowly making markets more efficient. We can speculate this is what we see as *ExcessReturns* decreases towards the end of our time series. Järf (2016)'s time-series ends in 2016 and this is also what the article speculates might happen.

[20]Indeed, at the end of the time-series the inflation adjusted average *FundSize* drops to about its 2008 level.

6 Conclusion

This thesis should highlight several aspects of scale and its role in Nordic markets. First, methodology is everything when investigating the effects of scale. Running regression based on estimators using OLS, OLS with FE, RD1 and RD2 we highlight the econometric pitfalls of scale, and how we avoid these. Using bias-free estimators we find empirical evidence for decreasing returns to scale at both the fund and industry-level in the Nordics. The results are also shown to be robust to several controls. Our findings coincide with findings in US markets by Pástor et al. (2015) and Zhu (2017).

When testing each sampled country individually, all countries apart from Denmark show decreasing returns to scale at the industry level. At the fund level Finland does not show statistically significant decreasing returns to scale, while Sweden shows increasing returns to scale. This can be connected to our quintile based regression which finds that the smallest funds do not show statistically significant decreasing returns to scale, while the largest funds show increasing returns to scale. This could be explained by smaller funds not having an adverse price impact and larger funds adjusting their investment strategy to better cope with decreasing returns to scale. Since Finland has a larger concentration of small funds, and Sweden a larger concentration of large funds this could explain the country-specific results.

We also find small-cap investing funds as well as funds with a higher turnover ratio and risk to have steeper decreasing returns to scale at the fund-level. We connect this to the theory of liquidity constraints from Berk and Green (2004). As the size of a fund increases, its returns are hampered by adverse price impacts in the underlying securities. A fund which invests in less liquid small-cap stocks and who has a higher turnover ratio therefore has a higher price impact as size increases. Based on existing literature we expected the determinants of industry decreasing returns to scale to be the same as for fund size. However, we find no evidence for this in the Nordics. We theorize that lower liquidity Nordic markets overall (compared to US markets) could explain why small-cap investors do not show steeper decreasing returns to scale in the Nordics.

Finally we find the Nordic mutual funds industry has become more skilled over time. This is driven mostly by the most and least skilled investors. However, because of an increase in industry size and an increase in the average size of each fund, this does not translate into higher excess return.

6.1 Further research

Our study contributes to the existing literature by examining scale and skill in a smaller market. It would also be interesting to see if decreasing returns to scale could be found in markets less liquid than the Nordics. Emerging markets would be an obvious candidate. In addition we find no evidence on the determinants of industry decreasing returns to scale in the Nordics. A closer look at this would also be interesting. Finally, we find indications of a nonlinear size-performance relation. A study which focuses more on different functional forms of fund size while using bias-free estimators would therefore also be of great interest to the literature.

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Appendices

A Figures and tables

Figure A.1: *FundSize* 12-month rolling average

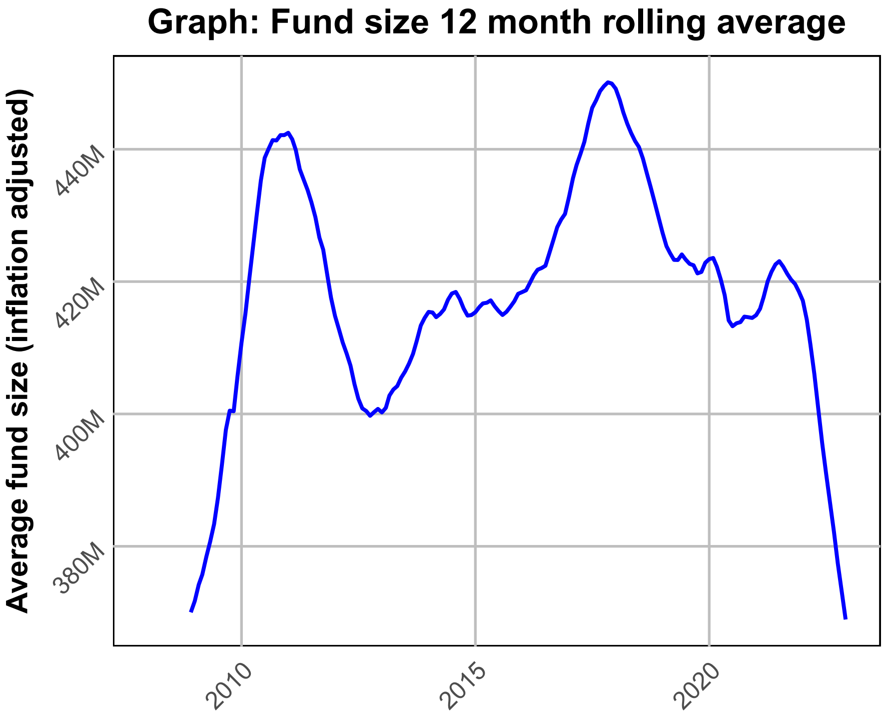

Figure A.2: *IndustrySize* 12-month rolling average

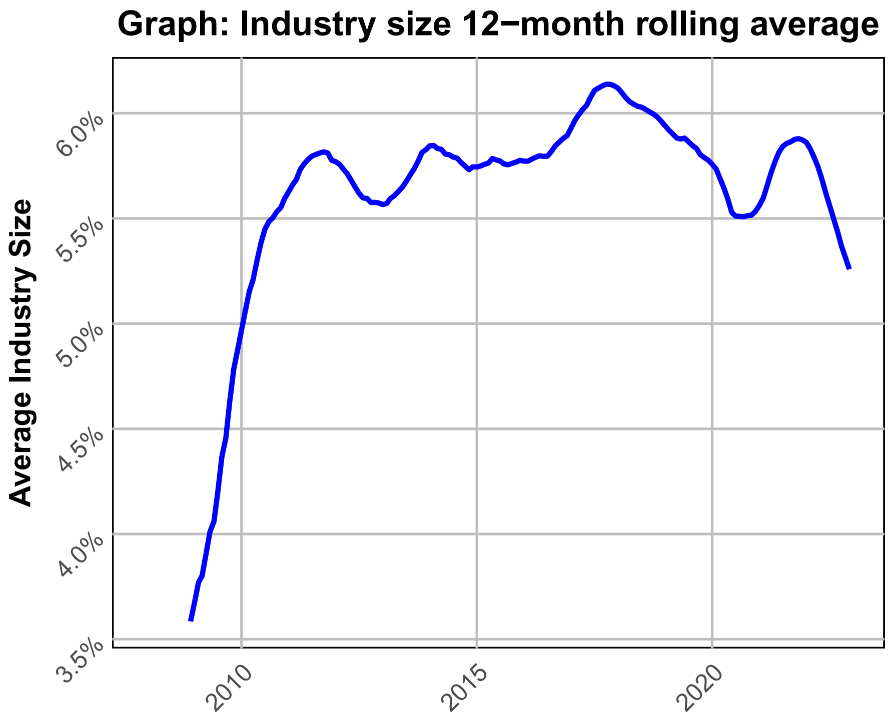

Figure A.3: *FundSize*

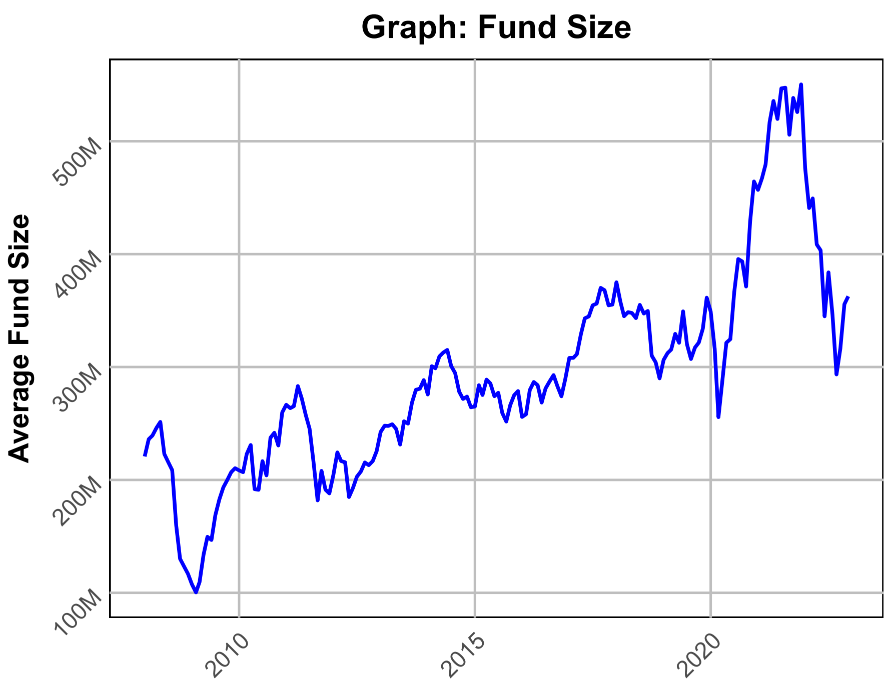

Figure A.4: Number of active funds

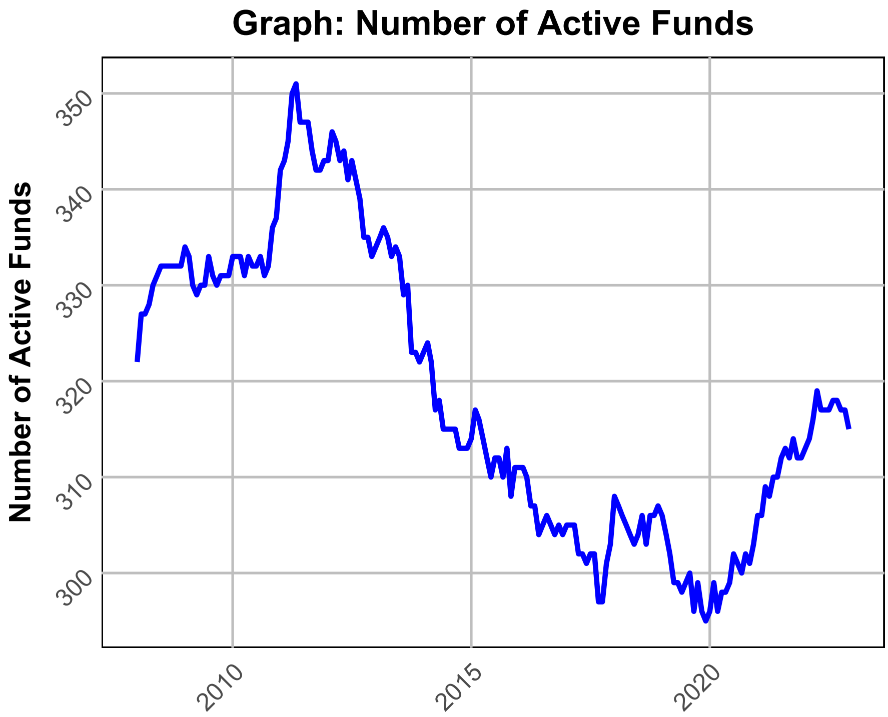

Figure A.5: Percentage of active small-cap firms

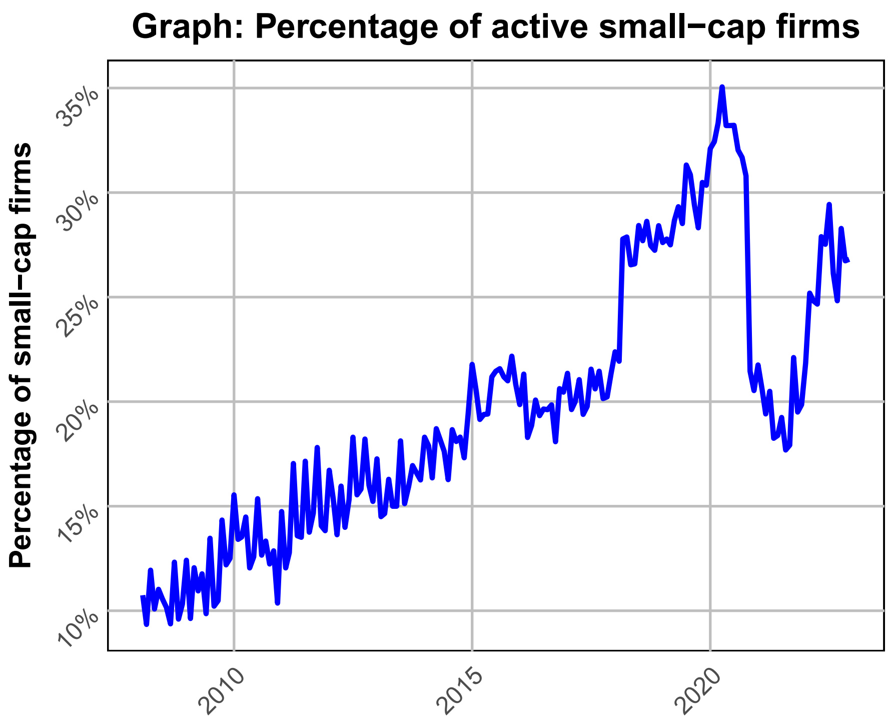

Figure A.6: Constant skill over time excluding *TurnoverRate*

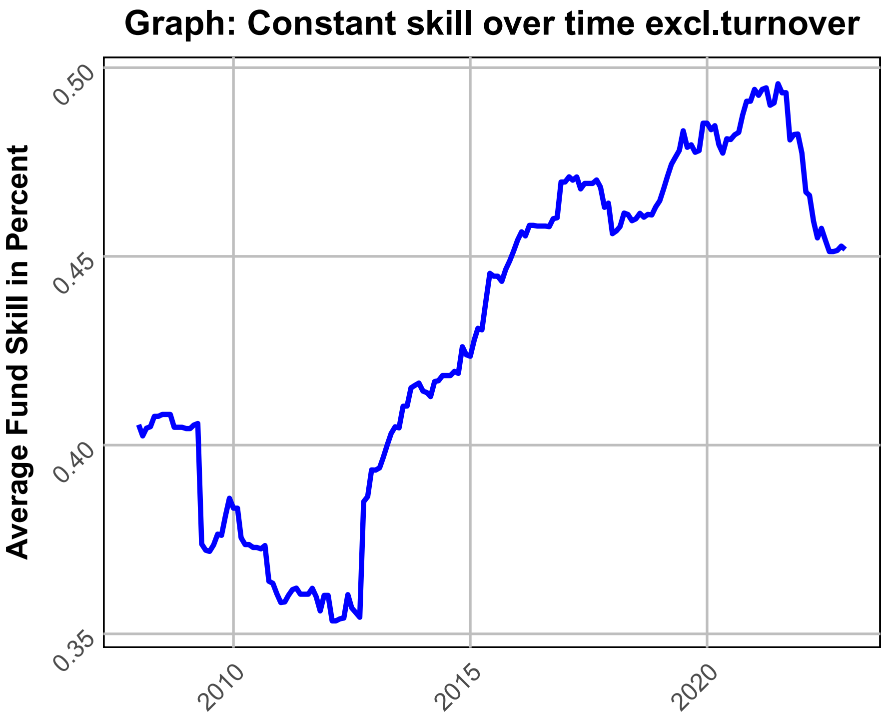

Figure A.7: Sector distribution 1st quintile

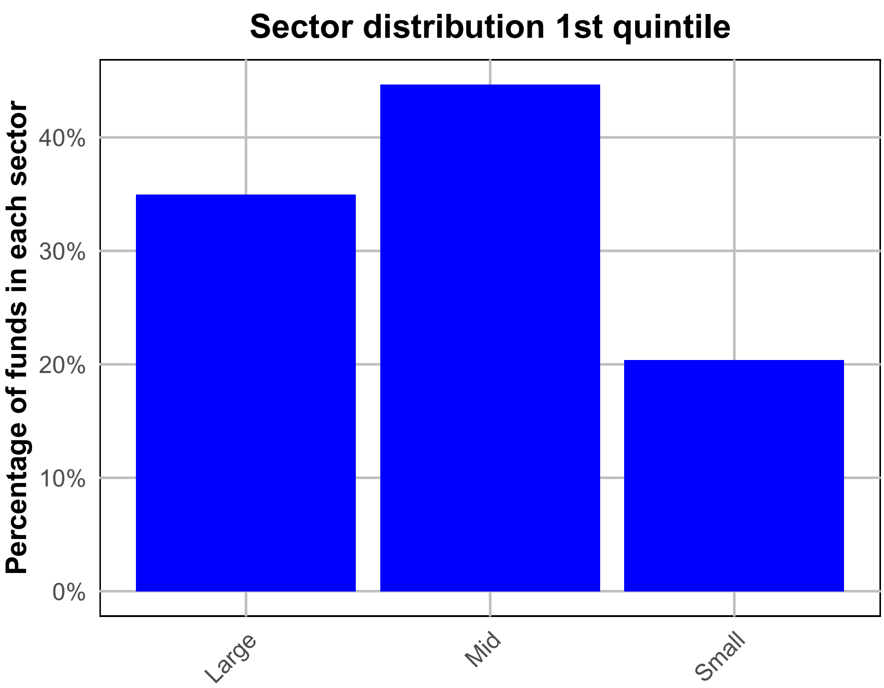

Figure A.8: Sector distribution 5th quintile

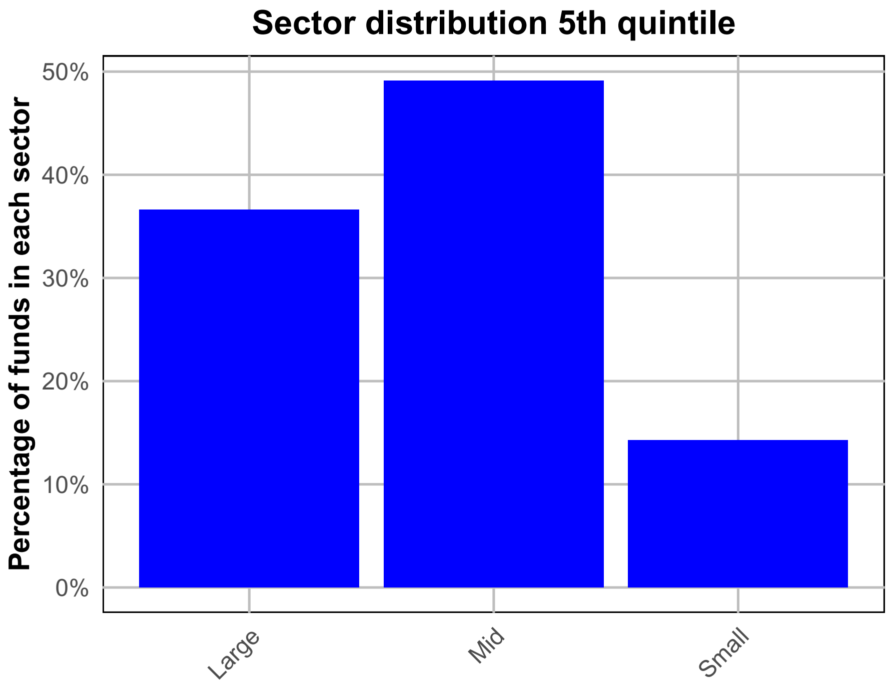

Table A.1: Interactions terms only for Norway

The dependent variable in all regressions is *ExcessReturn*, which is the fund's benchmark-adjusted gross return. *IndustrySize* is the total of all funds' AUM divided by total market capitalization for the corresponding month, presented in percentage. *1(SmallCap)* is a dummy-variable equal to one if the fund is trading small-capitalization stocks, and zero otherwise. *TurnoverRatio* is the lesser of purchases or sales divided by the average monthly net assets. *Risk* is residual of regressing excess gross return on the corresponding benchmark portfolio's return, for a 12-month rolling window. Heteroskedasticity robust standard errors are shown in parentheses. All variables are monthly observations.

	Dependent variable: *ExcessReturn*		
Variable	(1)	(2)	(3)
IndustrySize	-0.267	-0.269	-0.290
	(-5.82)	(-5.64)	(-6.69)
*IndustrySize*1(SmallCap)*	0.014		
	(0.49)		
*IndustrySize*TurnoverRatio*		0.0003	
		(2.52)	
*IndustrySize*Risk*			0.022
			(2.61)
Observations	7.926	6.885	9.180
R^2	0.4%	0.5%	0.5%
F Statistic	16.946***	18.239***	23.197***

Table A.2: Excluding foreign investors

The dependent variable in all regressions is *ExcessReturn*, which is the fund's benchmark-adjusted gross return. *IndustrySize* is the total of all funds' AUM divided by total market capitalization for the corresponding month, presented in percentage. *FundSize* is the fund's total assets under management for all share classes divided by total market capitalization, inflation adjusted and divided by 10 million. Heteroskedasticity robust standard errors are shown in parentheses. All variables are monthly observations.

	Dependent variable:		
Variable	(1) (RD2)	(2) (FE)	(3) (RD2)
FundSize	-0.003		-0.003
	(-2.59)		(-2.51)
IndustrySize		-0.095	-0.061
		(-6.56)	(-3.06)
Observations	45.377	49.037	45.377
R^2	0.01%	0.1%	0.04%
F Statistic	4.046***	35.401***	8.513***

Table A.3: Quintiles

The dependent variable in all regressions is forward demeaned *ExcessReturn*, where *ExcessReturn* is the fund's benchmark-adjusted gross return. *FundSize* is the fund's total assets under management (AUM) for all share classes divided by total market capitalization, inflation adjusted and divided by 10 million. Heteroskedasticity robust standard errors are shown in parentheses. All variables are monthly observations.

	Dependent variable: Forward demeaned *ExcessReturn*				
Variable	(1) Quintile 1	(2) Quintile 2	(3) Quintile 3	(4) Quintile 4	(5) Quintile 5
FundSize	-0.006	-0.036	-0.043	-0.076	0.002
	(-0.66)	(-5.16)	(-5.99)	(-9.16)	(2.09)
Observations	5.359	8.287	10.764	11.893	15.961
R^2	0.01%	0.3%	0.3%	0.7%	0.03%
F Statistic	0.441	26.670***	35.949***	84.020***	4.370***

Table A.4: *Log(FundSize)*

The dependent variable in all regressions is forward demeaned *ExcessReturn*, where *ExcessReturn* is the fund's benchmark-adjusted gross return. *IndustrySize* is the total of all funds' AUM divided by total market capitalization for the corresponding month, presented in percentage. *LogFundSize* is the fund's total assets under management for all share classes divided by total market capitalization, inflation adjusted, divided by 10 million and in the natural logarithm. *FamilySize* is the sum of FundSize within the same fund branding name. *MgrExp* represents the cumulative months of experience the fund manager possesses within their respective fund. *FundAge* is the monthly cumulative fund age, the start being their first offer date. *SectorSize* is the total AUM of all funds within a sector divided by the total market capitalization given that month, by the categories size (small-cap, mid-cap, and large-cap) and investment style (value, blend, and growth). Heteroskedasticity robust standard errors are shown in parentheses. All variables are monthly observations.

	Dependent variable: Forward demeaned *ExcessReturn*
Variable	(1)
Log(FundSize)	-0.006
	(-2.38)
IndustrySize	-0.011
	(-0.51)
FundAge	-0.001
	(-3.92)
FamilySize	-0.0003
	(-3.30)
SectorSize	-0.094
	(-1.32)
MgrExp	-0.0003
	(-0.94)
Observations	51.262
R^2	0.1%
F Statistic	8.805***