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Measuring Skill in the Nordic Hedge Fund Industry

An empirical study of the value Nordic hedge fund managers extract from financial markets

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Abstract

In this thesis, we use a unique dataset on Nordic hedge funds from January 2004 to August 2018 to investigate managerial skill in the Nordic hedge fund industry. Managerial skill is measured by the value hedge fund managers extract from financial markets, termed the *value added*.

To estimate the value added, we use a rolling window regression and regress unsmoothed hedge fund returns on the factors from an extension of the Fung-Hsieh 7-factor model. We find that the average Nordic hedge fund manager generates approximately $2 million (0.72% of avg. AUM) per month, while the median manager generates $0.5 million (0.18% of avg. AUM) per month. We document that Nordic hedge fund managers’ performance is persistent and therefore that managerial skill is present in the Nordic hedge fund industry. Nevertheless, we find cross-sectional differences in managerial skill between the top and bottom Nordic hedge fund managers. Further, we find that parts of the variation in the value added can be attributed to general hedge fund characteristics. Hence, the positive value added generated in the Nordic hedge fund industry is not solely a result of managerial skill.

Preface

This thesis is written as a part of our master's degree with a specialization in Financial Economics at the Norwegian School of Economics (NHH).

The thesis intends to examine managerial skill in the Nordic hedge fund industry, and the characteristics of the top performing funds. The topic selection is explained by our desire to write a quantitative paper, as well as our interest in financial markets and asset management. In addition, the growing attention of hedge funds in the media and the opening for small private investors in hedge funds have increased our interest in the topic.

The writing process has been both challenging and time consuming, but also educational and inspiring. Through our thesis we have had the opportunity to apply the knowledge we have acquired during our time at NHH.

We would gratefully like to thank our master thesis supervisor, Assistant Professor Nataliya Gerasimova, who has provided valuable feedback and guidance on a topic of which we initially had little knowledge. Furthermore, we would like to express our gratitude to HedgeNordic for providing us data and answering questions related to the Nordic hedge fund industry.

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1. Introduction

The global hedge fund industry has experienced a tremendous growth during the last decades. The Nordic hedge fund industry has followed a similar trend, and the number of hedge funds in the Nordics has reached a historical high of 180 hedge funds (HedgeNordic, 2018). The increased interest for hedge funds as an investment vehicle suggest that investors believe Nordic hedge fund managers are skilled. As of today, there is limited literature available on managerial skill in the Nordic hedge fund industry. The limited literature may be due to lack of available data on Nordic hedge funds. In this paper, we use a unique dataset on Nordic hedge funds from January 2004 to August 2018 to investigate managerial skill in the hedge fund industry.

In contrast to previous research on managerial skill in the hedge fund industry, we use the value hedge fund managers extract from financial markets as our measure of managerial skill, which Berk and Binsbergen (2015) have termed the *value added*. We consider the value added to be an appropriate measure of managerial skill for several reasons. First, we consider the argumentation provided by Berk and Binsbergen (2015) to be applicable to the hedge fund industry as well as the mutual fund industry. Secondly, as hedge funds aim for absolute returns and not relative returns, we find it more appropriate to use an absolute measure of managerial skill rather than a relative measure. Thirdly, unlike existing measures on managerial skill, the value added takes the fund size into account. When the fund size increases, relative measures of managerial skill are likely to decrease due to diseconomies of scale or because the hedge fund is not able to exploit the same profitable investment strategies as the fund size increases. We find this counterintuitive as we would expect the most skilled managers to attract the most capital and thereby control the largest hedge funds. Hence, we consider the value added to be an appropriate measure of managerial skill in the hedge fund industry as it is an absolute measure and it takes the fund size into account.

By using an alternative measure of managerial skill and with the utilization of the most recent data for the Nordic hedge fund industry, we will in this thesis examine the following research question:

> *What values are generated in the Nordic hedge fund industry, and is the value added a result of managerial skill?*

To examine our research question, we will investigate three hypotheses:

1. The average Nordic hedge fund manager generates a positive value added.
2. Nordic hedge fund managers generate a value added that is persistent.
3. The value added generated by Nordic hedge fund managers cannot be attributed to general hedge fund characteristics.

Our first hypothesis aims to measure the value Nordic hedge fund managers extract from financial markets. We start by running a rolling regression of hedge fund returns on the VIX factor and the seven factors from the Fung-Hsieh 7-factor model to estimate hedge fund alphas. The returns used for our rolling regression are adjusted by using Brooks and Kats' (2002) method of return unsmoothing. Based on the alpha estimates from the rolling regression, we compute monthly value added numbers for each hedge fund in our database. We find that the average Nordic hedge fund manager generates a value added of approximately \$2 million (0.72% of avg. AUM) per month, while the median manager generates \$0.5 million (0.18% of avg. AUM) per month. The positive value added estimate indicates that Nordic hedge fund managers generate a positive value added on average and this confirms our first hypothesis. However, as a positive value added is not necessarily a result of managerial skill, we test for persistence in the value added estimates to determine whether the value creation is a result of managerial skill or not.

The objective of our second hypothesis is to distinguish managerial skill from luck by examining persistence in the value added estimates. We start to test for persistence by comparing the performance of hedge fund managers sorted into deciles based on their skill ratio. From the test results, we conclude that the top managers consistently generate a positive value added, and that the bottom two deciles do not. Based on the test results, we conclude that there are cross-sectional differences in managerial skill between the top and bottom Nordic hedge fund managers, where the former group possesses managerial skill and the latter do not. Further, we follow Agarwal and Naiks' (2000) method to test for persistence due to potential econometric shortcomings of the first test. The method is based on a two-period framework, comparing hedge funds' skill ratio for sequential periods. We perform the test for three different measurement intervals and find that the value added estimates are persistent for all intervals. As a result, we can conclude that managerial skill is present in the Nordic hedge fund industry and that the conclusion is not sensitive to the number of observations we include in our measurement interval. Based on the results from the two persistency tests, we conclude that managerial skill is present in the Nordic hedge fund industry and this confirms our second hypothesis.

Our third hypothesis aims to assess if parts of the value added can be attributed to other factors than managerial skill. We examine the relationship between the value added and general hedge fund characteristics by regressing our monthly value added estimates on general hedge fund characteristics using univariate and multivariate regressions. Overall, the results show that parts of the value added can be attributed to general hedge fund characteristics. First, we find that older and more experienced hedge funds tend to generate a higher value added than younger and less experienced hedge funds. Secondly, our results show that Nordic hedge funds cannot justify a high management fee. We find the management fee to have a relatively large negative effect on the value added and a potential reason for this may be that investors are sensitive to the size of the fee. Thirdly, we find that hedge funds with a high-water mark perform better than those without it. A high-water mark prevents hedge fund managers from excessive risk-taking, and investors may find this attractive. Hence, a high-water mark can result in additional investments from investors, causing a potential higher value added. Fourthly, we find that the effect of having a minimum investment requirement is unknown as the univariate and multivariate regressions provide different results. Based on our findings, we reject our hypothesis of fund characteristics having no effect on the value added. Hence, hedge funds with certain characteristics are performing better than others, for a given level of managerial skill. However, as the characteristics' explanatory powers are small, these results do not change our conclusion of managerial skill being present in the Nordic hedge fund industry.

In sum, we find evidence of Nordic hedge fund managers generating a positive value added due to managerial skill. However, the positive value added is not solely a result of managerial skill, as parts of the value added can be attributed to general hedge fund characteristics.

The rest of the thesis will proceed as follows. Section 2 summarizes previous literature on factor models, measures of managerial skill and the relation between fund characteristics and hedge fund performance. Section 3 presents our hypotheses regarding managerial skill and fund characteristics in more detail, and in Section 4 we provide theory on hedge fund characteristics. Section 5 presents the empirical methods we use examine our hypothesis, while Section 6 provides explanations of the hedge fund data and risk factor data. Section 7 presents the results from the study, followed by Section 8 where we summarize our main findings.

2. Literature Review

This paper contributes to the existing literature on hedge funds in two ways. First, the Nordic hedge fund industry is not a well-covered topic in the literature. A potential reason for this may be due to lack of data available on the Nordic hedge fund industry. The lack of Nordic hedge fund data available is mainly because hedge funds are restrictive in disclosing their fund information to the public and that hedge funds are a relatively new phenomenon in the Nordics. Secondly, to our knowledge there are no other studies on hedge funds that use value added as a measure of managerial skill in the hedge fund industry. In this paper, we focus on Nordic hedge funds and we use a new approach to measure managerial skill in the hedge fund industry.

In the following section we first present existing literature related to factor models and risk factors used to assess hedge fund performance. Then we present previous research on managerial skill in the hedge fund industry, and the most relevant studies examining the relationship between hedge fund characteristics and fund performance.

2.1 Factor Models

To measure the value hedge funds extract from financial markets, hedge fund performance can be compared to the performance of the second-best investment opportunity for investors, referred to as the benchmark. There are two common approaches to evaluate hedge fund performance. The first approach is referred to as the benchmark approach and involves selecting an alternative investment opportunity as a benchmark, e.g. HFRI Index, S&P500 Index etc. (Berk & Binsbergen, 2015). The second approach is called the traditional risk-based approach. In the literature, it is normal to assume that the riskiness of a hedge fund can be measured through identified risk factors (Berk & Binsbergen, 2015). Under this assumption, the benchmark return of a hedge fund equals the return of an equally risky portfolio constructed using identified risk factors. As the identified risk factors do not necessary represent actual investable alternatives, the risk-based approach is considered to be an adjustment for risk rather than a benchmark (Berk & Binsbergen, 2015). We only consider the risk-based approach in this paper as this is the most common approach among researchers.

To identify appropriate risk factors, a natural starting point is to examine if hedge funds are exposed to the market or systematic risk. Older studies conclude that hedge funds are market neutral as they find evidence of low correlation between hedge fund returns and market returns, or with a set of specified risk factors (Liang, 1999). The evidence of low correlation between hedge fund performance and a set of specified risk factors indicates that factor models are inappropriate in explaining hedge fund performance. Later studies have revisited the claim of market neutrality in the hedge fund industry, and Patton (2009) finds evidence of only 25% of the so-called market neutral hedge funds actually being market neutral. The fact that only 25% of hedge funds being market neutral suggests that most hedge funds are exposed to some sort of systematic risk, thus most hedge funds are expected to have non-zero betas.

If hedge funds are not market neutral, hedge funds are exposed to some sort of systematic risk that predicts their performance (Bali, Brown & Caglayan, 2012). Bali, Brown, and Caglayan test this idea by estimating individual hedge funds' exposure to various risk factors. They find that hedge fund performance is largely determined by exposure to systematic risk, while residual risk has no predictive power.

Given the evidence of hedge funds being exposed to systematic risk, the literature presents two approaches to attribute hedge fund performance to risk factors (Agarwal, Mullally & Naik, 2015). The first approach, presented by Agarwal, Mullally, and Naik, involves identifying pre-specified risk factors that can explain hedge fund performance. The second approach they describe uses underlying assets to identify sources of hedge funds performance. That involves replicating hedge funds' portfolios by trading underlying assets, where the constructed trading factors are named asset-based style factors (Fung & Hsieh, 2002).

While there is an extensive literature on how to assess hedge fund performance, there is no consensus in the literature on which factors to include in a factor model. For that reason, we describe factors and factor models that are commonly used in the literature to assess hedge fund performance.

Previous research suggests that single factor models have difficulties in explaining hedge fund performance. A study conducted by Kazemi, Martin, and Schneeweis (2001) finds that the CAPM has low explanatory power and that the CAPM is not properly able to measure the riskiness of hedge funds. Similarly, Favre and Ranaldo (2005) find that the CAPM (Sharpe, 1964) has difficulties in explaining past superior performance of hedge funds. Based on CAPM's difficulties in explaining hedge fund performance, Kazemi, Martin, and Schneeweis (2001) argue that multifactor models are better in explaining the riskiness of hedge fund returns.

More recent literature applies multifactor models to examine hedge fund performance. Examples are the Fama-French 3-factor model (1993) and the Carhart 4-factor model (1997). These models include several risk factors to provide a better understanding of the risk-performance relationship in hedge funds. Agarwal and Naik (2004) find evidence of hedge funds exhibiting risk exposure to the Fama-French factors, and to the additional momentum factor included in the Carhart model. Their finding support Kazemi, Martin, and Schneeweis' (2001) argument, that multifactor models can explain variation in hedge fund performance.

Fung and Hsieh (1997) find that hedge funds exhibit non-linear exposure to standard asset classes due to their use of dynamic trading strategies, which can give rise to option-like payouts. As a result, they claim that traditional linear factor models, such as the CAPM, Fama-French, and Carhart, are inappropriate in explaining hedge fund performance. Hence, they propose an asset-based 7-factor model that aims to replicate hedge fund portfolios by trading underlying assets. Fung and Hsieh (2004) find evidence of the 7-factor model explaining up to 80% of the variation in hedge fund returns. Later, two additional trend-following factors have been added to improve the 7-factor model.

More recently, researchers have moved their attention to uncover additional risk factors that can explain hedge fund performance. As the literature has uncovered several risk factors that affect hedge fund performance, we only present previous studies on the factors we use in latter parts of this paper. Capocci and Hübner (2004) study if hedge fund performance is affected by investments in emerging markets. They find evidence of an emerging market factor affecting hedge fund performance. Avramov, Barras, and Kosowski (2013) examine the relationship between macroeconomic variables and hedge fund performance. Their results show that hedge fund performance being related to the aggregate market volatility, termed the VIX factor. Ilerisoy, Sa-Aadu, and Tiwari (2017) explore the relationship between hedge fund performance and funding liquidity risk. They include the TED spread in their factor model and find evidence of funding liquidity risk affecting hedge fund performance.

The key takeaway from the presented literature is that the universe of factor models and factors explaining hedge fund performance is broad, and that the universe is still expanding as more data is available on hedge funds.

2.2 Managerial Skill

2.2.1 Performance

“Manager skill is usually thought to be manifested in the alpha, or the portion of a fund’s return not attributed to systematic risk exposures” (Agarwal, Mullally & Naik, 2015). If a hedge fund manager possesses managerial skill, we would expect that skill to emerge as a positive alpha (Pedersen, 2015).

Early studies find evidence of significantly positive alphas in the hedge fund industry. Ackermann, McEnally, and Ravenscraft (1999) document that hedge funds consistently outperform mutual funds in the period of 1988-1995, and that incentive fees partly explain the superior performance. Later, Edwards and Caglayan (2001) estimate alphas for individual hedge funds for the period 1990-1999. They find that approximately 25% of the hedge funds earn a positive alpha, and that the frequency and size of positive alphas differ substantially between different investment styles. Based on these two studies, it appears managerial skill exist in the hedge fund industry.

In more recent studies, hedge fund performance has been studied in greater detail. There is evidence of positive alphas for a majority of the hedge fund strategies when applying the Fung-Hsieh 7-factor model (Agarwal, Bakshi & Huij, 2009). Based on daily transaction data, Jame (2012) finds no evidence of outperformance among the average hedge fund, for holding periods ranging from one to twelve months. However, the author emphasizes that the performance of the top performing hedge funds cannot be attributed to chance alone. Kosowski, Naik, and Teo (2007) use a robust bootstrap methodology and the Fung-Hsieh 7-factor model to study hedge fund performance. They find that the performance of the top performing hedge funds cannot be explained by luck alone, which is consistent with Jame’s findings. Together, these two studies prove that managerial skill exists among the top performing hedge funds.

Although many of the above-mentioned studies find evidence of positive alphas in the hedge fund industry, there is no consensus regarding the existence of positive alphas in the hedge fund industry. Zhong (2008) argues in his paper that the aggregate level of hedge fund alphas has decreased during the 2000s. He bases his argumentation on a seemingly decreasing fraction of hedge funds being capable of producing positive alphas rather than an increasing fraction of unskilled managers producing negative alphas. Zhong’s finding implies that there is a decreasing trend in managerial skill among hedge funds.

There are several research papers that rely on alternative methods to study the alpha to determine whether or not a hedge fund manager is skilled. Chen, Cliff, and Zhao (2017) use the expectation-maximization algorithm to infer managerial skill. By assuming that managers fall into a discrete number of skill categories, they infer the percentage of managers in each category using the observed distribution of alphas. Their results indicate that approximately 50% of all hedge fund managers possess skills. Cao, Farnsworth, and Zhang (2014) provide another way to identify managerial skill. The authors' hypothesis is that if a manager launches a fund of a given strategy that has low flows or returns, the manager is likely to be in the possession of skill. Conversely, new funds are launched to satisfy investor demands for strategies with high flows or returns. Their findings confirm their hypothesis that skill-driven launches outperform demand-driven launches by approximately 4-5% per year. These findings suggest that certain hedge managers are skilled, but not necessarily all of them.

The literature highlights that the most common sources of managerial skill are asset-picking and market timing abilities (Pedersen, 2015). Brunnermeier and Nagel (2004) were some of the first to study asset-picking and market timing abilities among hedge funds, and their findings suggest that hedge fund managers possess both abilities. Later, French and Ko (2006) provide evidence of asset-picking abilities among hedge fund managers, but they find limited evidence of market-timing abilities. Griffin and Xu (2009) use hedge fund company holdings to detect the presence of managerial skill and find evidence of hedge fund managers not being more skilled than mutual fund managers. Similarly, Cao et al. (2016) use hedge fund company holdings to examine whether or not hedge funds possess managerial skill. They conclude that superior hedge fund performance can be attributed to hedge funds ability to manage downside risk rather than asset-picking or market timing abilities.

Contrary to the studies presented, Berk and Binsbergen (2015) argue that the alpha does not measure managerial skill. They state that the gross alpha is a return measure, not a value measure. Just as the internal rate of return cannot be used to value an investment opportunity, the gross alpha cannot be used to value a fund. To exemplify this argument, Berk and Binsbergen (2015) state that it is unclear whether a fund manager generating a 1% return on a $1 billion fund is more skilled than a fund manager generating 10% return on a $1 million fund. Nevertheless, they argue that the alpha would be an appropriate measure of managerial skill if all funds are the same size. The size argument is based on investor competition driving net alpha to zero. Berk and Green (2004) state that "if skill is in short supply, the net alpha is determined in equilibrium by competition between investors, and not by the skill of managers". Hence, the net alpha does not represent managerial skill.

Berk and Binsbergen (2015) argue that the net alpha is a measure of abnormal return, not a measure of managerial skill. They argue that the net alpha does not reflect managerial quality, rather it measures the rationality and competitiveness of financial markets. If financial markets are competitive and investors rational, then the net alpha will equal zero. Similarly, the net alpha will be non-zero if these conditions are violated.

To account for the aforementioned weaknesses of using alpha as a measure of skill, Berk and Binsbergen (2015) suggest using the value that funds extract from financial markets as a measure of managerial skill. They term this measure the value added. For our analyses, we use Berk and Binsbergens' approach and use value added as our measure of managerial skill.

2.2.2 Persistence

Although previous research finds evidence of positive alphas in the hedge fund industry, that does not necessarily imply that hedge fund managers are skilled. The positive alphas could also be a result of lucky managers or model uncertainty (Agarwal, Mullally & Naik, 2015). Researchers have addressed this problem by studying persistence in hedge fund performance, and they conclude that hedge fund managers are being skilled if their performance is persistent.

Previous research concludes that persistence in hedge fund performance is scarce, and if present, it only lasts for a short period of time. Agarwal and Naik (2000) examine whether or not performance persistence is sensitive to the length of return measurement intervals by using a multiperiod framework. Their results indicate that persistence is short-term in nature, and that the maximum persistence is present at quarterly horizons. Baquero, Horst, and Verbeek (2005) correct for a multiperiod sampling bias and investment styles when analyzing persistence in hedge fund performance. Their results show positive persistence in hedge fund returns, at quarterly levels. Similar results are presented at annual level, but with weak statistical significance. Together, these results suggest that managerial skill is scarce and short-term in nature.

Kat and Menexe (2003) study hedge fund persistence and predictability of statistical parameters and find little evidence of persistence in mean returns. However, the authors find evidence of persistence in hedge funds' standard deviation and correlation to the stock market. A more recent study, solely based on past performance of funds, finds no evidence of persistence in hedge fund performance (Boyson, 2008). However, by including data on manager experience in addition to the data on past performance, Boyson finds evidence of quarterly persistence for funds with low tenure and past good performance. These two studies support the findings above, that managerial skill is present in the short-term.

Other research finds persistence in hedge fund performance at annual horizons. Caglayan and Edwards (2001) studied individual hedge funds from 1990 to 1998 by estimating fund alphas. The authors find evidence of persistence over a 1-year and 2-year horizon for both the best and worst performing hedge funds. Kosowski, Naik, and Teo (2007) examine performance persistence by forming hedge fund portfolios based on hedge funds' corresponding alpha deciles. The authors compare the alpha and corresponding t-statistic for the top and bottom decile to examine persistence, and they find that hedge fund performance is persistent at annual horizons. By employing the generalized method of moments (GMM) and the weighted least squares (WLS) to predict future relative fund performance, Jagannathan, Malakhov, and Novikov (2010) find that hedge fund performance is persistent at a 3-year horizon and that persistence is largely explained by the top performing hedge funds. The results indicate that cross-sectional differences exist in hedge fund managers' performance.

2.3 Hedge Fund Characteristics

Researchers find evidence of hedge fund characteristics explaining cross-sectional variations in hedge fund performance (Agarwal, Mullally & Naik, 2015). Consequently, many researchers have moved their attention toward hedge fund characteristics, such as fees, minimum investment requirements, country of registration and assets under management, to examine the direct impact of such features on hedge fund performance. As Anderson, Stafylas, and Uddin (2016) state: "There is also a relationship between certain hedge fund characteristics and performance." In the following, we present prior studies on some of the fund characteristics we use for further analyses.

Liang and Schwarz (2011) use pay-performance sensitivity to examine the effect of fund size (AUM) on hedge fund performance. They find that fund size affects hedge fund performance positive up to a point where the relation turns negative. A potential reason for the negative relation between fund size and performance can be diseconomies of scale, by hedge fund performance decreasing after a certain fund size is reached. Yin (2013) examines how the agency problem between hedge fund managers' desire to increase AUM and investors' desire to maintain high performance impacts fund size. As hedge fund managers' compensation is largely determined by the size of the fund, they have incentives to increase AUM up to a point at which investors withdraw their capital due to bad performance. Other hedge fund managers may increase AUM because of empire building ambitions, i.e., to gain a higher status in the financial markets. Based on his study, Yin concludes that agency problems exist in the hedge fund industry as hedge fund managers maximize their own compensation rather than fund performance. These results imply that hedge fund performance is negatively related to fund size.

Early studies conclude that the compensation structure in the hedge fund industry provides managerial incentives to achieve high fund returns (Agarwal, Mullally & Naik, 2015). For the period from 1992 to 1996, Liang (1999) examines if the fee structure of hedge funds is designed to align managers' incentives with investors' interests. He finds a positive relationship between hedge fund performance and managers' performance fees and concludes that the interests of managers and investors are aligned. Further, Liang finds that hedge funds with high-water mark provisions perform significantly better than hedge funds without, and that hedge fund performance is negatively related to fund age. Caglayan and Edwards (2001) confirm these findings, by using monthly data on hedge fund returns for the period 1990-1998. They find that performance fees and age are positively related to performance, and that management fees are negatively related to hedge fund performance. Agarwal, Daniel, and Naik (2009) find that high-water mark provisions and performance fees are associated with superior hedge fund performance, and that hedge fund performance is negatively correlated to fund size, age and management fees. In sum, these authors find that performance fees and high-water mark provisions have a positive effect on hedge fund performance, that management fees and fund size have a negative effect, and that the effect of fund age is ambiguous.

Other researchers claim that there is no relationship between compensation structure and hedge fund performance. Based on an analysis of Asian hedge funds, Koh, Koh, and Teo (2003) conclude that there exists an insignificant negative relationship between hedge fund performance and fee levels and minimum investment requirements. Kouwenberg and Ziemba (2007) study how performance fees and managers' own investments in hedge funds affect hedge fund performance. The authors find that there is an insignificant and negative relationship between fee levels and hedge fund performance. Contrary to the previous presented literature, these authors find no evidence of fund fees having an effect on hedge fund performance.

3. Hypotheses

In this section, we describe our three hypotheses regarding the Nordic hedge fund industry. The first two hypotheses are related to the presence of managerial skill in the Nordic hedge fund industry, and the last hypothesis is related to how general hedge fund characteristics influence the value added.

3.1 Hypothesis 1

Hypothesis 1: The average Nordic hedge fund manager generates a positive value added.

We expect the average Nordic hedge fund manager to generate a positive value added. If hedge fund managers do not generate a positive value added, we would expect investors not to invest in this type of investment vehicles. With investors unwilling to invest, hedge funds would not continue to operate due to lack of capital. Although we expect hedge funds to deliver a positive value added on average, that does not imply that all hedge funds generate a positive value added in each period. In the short term, we believe that some hedge funds generate a negative value added, but in the long term they all have to generate a positive value added to survive. Previous research finds that hedge funds on average generate a positive alpha, but that there has been a downward trend in the alpha in recent years. Since the value added is equal to the product of assets under management and the alpha, and assets under management cannot be negative, we expect the average monthly value added to be positive.

3.2 Hypothesis 2

Hypothesis 2: Nordic hedge fund managers generate a value added that is persistent.

The increased interest for hedge funds as an investment vehicle may suggest that investors believe that Nordic hedge fund managers are in the possession of managerial skill. If Nordic hedge fund managers are skilled, we expect them to persistently generate a positive value added. If the value added figures are not persistent, the generated value added can be a result of luck rather than managerial skill. Previous research documents hedge fund performance to be persistent in the short term. As we consider the global hedge fund industry to be rather homogenous, we expect Nordic hedge fund managers to persistently generate a positive value added. Based on the increased interest in the industry and the previous research, we expect Nordic hedge fund managers to be in the possession of managerial skill.

3.3 Hypothesis 3

Hypothesis 3: The value added generated by Nordic hedge fund managers cannot be attributed to general hedge fund characteristics.

If two managers possess the same level of managerial skill, we expect them to generate an equally large value added on average, irrespective of the general hedge fund characteristics. Hence, we do not expect the value added to be attributed to general hedge funds characteristics. Another reason for why we believe our hypothesis is true, is that some of the fund characteristics are easy to change. Therefore, we believe that hedge funds would have changed their fund characteristics if there had been evidence of certain fund characteristics performing better than others. For these reasons, we expect general hedge fund characteristics to have an insignificant impact on the value added.

There is no consensus in the existing literature regarding how hedge fund characteristics can be attributed to hedge fund performance, except from several findings of management fees having a negative effect. As we have little variation in our data on management fees, we do not expect to find a negative effect on the value added. Thus, we expect general hedge fund characteristics to have no effect on the value added generated by Nordic hedge fund managers.

4. Hedge Funds

In this section we define what a hedge fund is and describe the most prominent features of a hedge fund. To evaluate managerial skill in the Nordic hedge fund industry, we conduct several data adjustments related to certain hedge fund characteristics. In addition, this section builds the foundation of our third hypothesis, examining the relationship between hedge fund characteristics and value added.

4.1 Hedge Fund Definition

There is no universal definition of hedge funds. Lhabitant (2004) defines hedge funds in the following way:

> Functionally, hedge funds and proprietary trading desks pursue similar goals: hiring professional investment managers, rewarding them by performance-linked fee and implementing a large diversity of strategies often involving leverage, derivatives, hedging and short positions to exploit market inefficiencies. Organizationally, however, there are substantial differences: hedge funds are typically private pooled investment vehicles with high minimum investments and infrequent redemption opportunities.

Although there is no common definition of hedge funds, hedge funds have several unique characteristics, such as their aim for absolute returns, their managerial compensation structure, the light regulatory environment, flexibility and so on. However, the extent of these characteristics varies greatly from one hedge fund to another.

4.2 Absolute Returns

One of the main differences between hedge funds and mutual funds is that hedge funds aim for absolute returns rather than relative returns. With the aim for absolute returns, hedge funds can earn positive returns regardless of benchmark performance and market conditions (Siegel & Waring, 2006). Hence, hedge funds should be able to produce positive returns in both bull and bear markets, i.e., hedge funds are hedging the market risk under all market conditions. Consequently, hedge funds should only be exposed to unsystematic risk. With the aim of absolute returns, hedge funds normally have less downside risk and higher upside return compared to relative-return investments (Siegel & Waring, 2006).

4.3 Investments

To achieve the absolute return target, hedge funds are given the flexibility to choose among various asset classes and to employ dynamic trading strategies that involve short sales, leverage, illiquid assets and derivatives (Fung & Hsieh, 1997). By employing dynamic trading strategies hedge funds try to exploit market inefficiencies to outperform the target return, which implies they pursue an active investment strategy (Liang, 1999). Despite their flexibility in investing, hedge funds are required to act in accordance with their fund mandates, as well as financial regulations. Since hedge funds employ a wide array of investment strategies, they are usually classified according to their investment style, such as opportunistic, global/macro, value etc. (Fung & Hsieh, 1997). The different investment styles apply different investment approaches and there exist large variations in return and risk among hedge funds. The variation in return and the potential high risk for investors have resulted in restrictions for hedge funds to advertise their services.

4.4 Investor Criteria

Generally, investors have to meet several criteria to be able to invest in hedge funds. Hedge funds are usually only available to “accredited” or qualified investors, i.e., investors have to meet an income or net worth requirement to be able to invest in hedge funds (Ganchev, 2014). The requirements are set by tax authorities, but some hedge funds choose to set higher requirements for their investors. As an example, the United States requires individual hedge fund investors to have an annual income that exceeds $0.2 million for the past two years or a net worth exceeding $1 million (Ganchev, 2014). In addition to the above-mentioned criteria, most hedge funds also operate with minimum investment requirements (Liang, 1999). The role of this requirement is to control hedge funds’ investor base, where a high minimum requirement is likely to correspond to a high proportion of institutional investors.

Furthermore, it is not unusual that hedge funds impose non-discretionary restrictions on capital withdrawals in the form of a lock-up, redemption and notice period (Agarwal, Mullally & Naik, 2015). The lock-up period refers to the time window investors are restricted from withdrawing the capital they have invested, the redemption period is the frequency at which investors can withdraw their capital, and the notice period refers to the amount of time that the investor must provide the hedge fund manager before the capital is withdrawn (Agarwal, Mullally & Naik, 2015). The aim of these restrictions is to prevent investors from immediate withdrawals, as some hedge funds hold investments that are highly sensitive to illiquidity (Liang, 1999).

Based on the different investor criteria, it seems like hedge funds only are available to wealthy investors. However, in recent years we have seen a development of funds of hedge funds. These types of funds have opened for less wealthy investors to invest in hedge funds.

4.5 Fees

Hedge funds typically charge their investors both a management fee and a performance fee. The management fee is calculated as a percentage of a hedge fund's net asset value, typically of 1-2% of assets under management. The role of the management fee is to cover operating costs of hedge funds rather than generating profit (Ganchev, 2014). Nevertheless, there are some larger hedge funds generating high economic profits from management fees due to economies of scale (Ganschev, 2014). To generate profits, hedge funds charge their investors a performance fee of typically 20% of their annual profits. The intension of the performance fee is to motivate hedge fund managers to strive for high positive returns (Ganchev, 2014).

By itself, the performance fee creates incentives for excessive risk-taking among hedge fund managers. As a result, most hedge funds have introduced a high-water mark system or a hurdle rate to reduce managers' incentives for excessive risk-taking and to attract investors. A high-water mark system implies that a hedge fund is only allowed to charge a performance fee if the fund's value surpasses its historical peak (Shin, Smolarski & Soydemir, 2017). The high-water mark system prevents hedge fund managers from receiving fees for volatile performance, therefore they have incentives to take less risk. However, the high-water mark system also provides hedge fund managers incentives to close funds that have suffered serious losses in the past and instead open new funds, rather than attempting to recover these losses. Therefore, a high-water mark system can result in frequent changes in the industry. Other hedge funds include a hurdle rate that represents the minimum return a hedge fund manager has to achieve to receive the performance fee (Shin, Smolarski & Soydemir, 2017). Typically, the hurdle rate is set relative to a benchmark rate or to a fixed percentage.

4.6 Regulation

Unlike mutual funds, the majority of hedge funds are not subject to regulations as they typically are organized as limited partnerships or limited liability companies. As most hedge funds are private and unregistered, they do not face standard reporting requirements (Maxam et al., 2005). Consequently, these types of hedge funds do not classify as investment vehicles since they do not meet the required levels of accountability and transparency (Maxam et al., 2005). As a result, most hedge funds are not obliged to disclose their holdings or investment strategy. By not disclosing fund information hedge funds can achieve confidentiality for their investments and protect themselves against competition. Nevertheless, it is worth noting that some countries have introduced hedge fund regulations, such as reporting requirements, to mitigate the risk induced by hedge funds and to protect investors (Fagetan, 2012).

4.7 Return Smoothing

Many hedge funds invest in illiquid assets and assets that are difficult to value due to their flexibility in investing. For example, real estate, stocks quoted on the OTC, and bonds quoted in emerging markets (Gallais-Hamonno & Huyen, 2007). By investing in this kind of assets, hedge funds can smooth their returns by overvaluing or undervaluing the assets in which they are positioned. Missing and/or outdated asset prices enable hedge funds to smooth their returns. Hedge funds perform this kind of return smoothing to appear less volatile by distributing losses over time. As a result, the reported returns of hedge funds appear smoother than their real economic returns. Hence, return smoothing can potentially result in an overestimation of the returns and a downward bias in the estimated variance due to autocorrelation (Gallais-Hamonno & Huyen, 2007).

5. Methodology

In this section, we present the empirical methods and factor models we use to examine our hypotheses. First, we describe the factor models we use to assess hedge fund performance, followed by a description of a method to unsmooth reported returns and a method for testing funds' factor exposure. Then, we present how we test for managerial skill in the Nordic hedge fund industry by presenting two persistence tests.

5.1 Factor Models and Correction Methods

We start by presenting five factor models that are commonly used to assess hedge fund performance. Next, we present Brooks and Kats' (2002) method to adjust for return smoothing. The consequence of not adjusting for return smoothing, if present, is an overestimation of the returns and a downward bias in the estimated variance due to autocorrelation. Finally, we present Shin, Smolarski, and Soydemirs' (2018) method to test for time-varying factor exposure. The consequence of not adjusting for time-varying factor exposure is biased estimates.

5.1.1 Factor Models

The five factor models we use to assess hedge fund performance are CAPM, Fama-French 3-factor model, Carhart 4-factor model, and Fung-Hsieh 7-factor and 9-factor model. By selecting this combination of models, we investigate if traditional asset pricing models are better in explaining hedge fund performance compared to models specifically designed for hedge funds, the Fung-Hsieh models. To evaluate which model best explains the performance of Nordic hedge funds we run Ordinary Least Squares (OLS) regressions on time series data.

CAPM

The single index model is based on the Capital Asset Pricing Model (CAPM), and it reveals a fund's excess return in terms of the market. The alpha is interpreted as a measure of out- or under-performance relative to a benchmark on a monthly basis (Sharpe, 1964). Formally, the single index model can be expressed as:

$$R_{it} - R_t^F = \alpha_i + \beta_i^M [R_t^M - R_t^F] + \varepsilon_{it}, \tag{1}$$

where R_{it} = return of fund i at time t, α_i = risk adjusted excess return of fund i, β_i^M = fund i's exposure to the market (systematic risk), R_t^M = market return at time t, R_t^F = risk-free rate at time t, and ε_{it} = error term of fund i at time t (unsystematic risk).

Fama-French 3-Factor Model

The Fama-French 3-factor model is an extension of the CAPM. In addition to the market factor, the model includes the two factors "Small Minus Big" (SMB) and "High Minus Low" (HML). The size factor (SMB) is the returns of a fund taking long positions in small capitalization firms and short positions in high capitalization firms, while the value factor (HML) is the returns of a fund taking long positions in firms with high book-to-market value (value) and short positions in low book-to-market (growth) firms (Fama & French, 1993). By including the Fama-French factors, we get:

$$R_{it} - R_t^F = \alpha_i + \beta_i^M [R_t^M - R_t^F] + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \varepsilon_{it}, \qquad (2)$$

where SMB_t = size factor at time t, HML_t = value factor at time t, β_i^θ = fund i's factor exposure to θ, and θ = respective risk factors in the model.

Carhart 4-Factor Model

The Carhart 4-factor model adds a momentum factor (MOM) to the Fama-French 3-factor model. The momentum factor is the returns of a fund taking long positions in past "winning" firms and short positions in past "losing" firms (Carhart, 1997). The Carhart 4-factor model can be expressed as:

$$R_{it} - R_t^F = \alpha_i + \beta_i^M [R_t^M - R_t^F] + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \beta_i^{MOM} MOM_t + \varepsilon_{it}, \qquad (3)$$

where MOM_t = momentum factor at time t, β_i^θ = fund i's factor exposure to θ, and θ = respective risk factors in the model.

Fung-Hsieh 7-factor model

The Fung-Hsieh 7-factor model is a nonlinear factor model based on asset-based risk factors. The model includes two equity factors, two fixed-income factors and three trend-following factors. The two equity factors have the same interpretations as the market and size factor in the Fama-French 3-factor model. The first fixed-income factor represents the returns of a fund taking long positions in the bond market, while the second represents the returns of a fund taking long positions in bonds with low credit ratings or liquidity, and short positions in bonds with high credit ratings or liquidity (Fung & Hsieh, 2004). The three trend-following factors represent the returns of a fund making bets on volatility in respectively the fixed-income, currency and commodity market (Fung & Hsieh, 2004). The trend-following factors aim to capture the largest price movements within a time interval, so they all have similar payout structures to lookback straddle options (Fung & Hsieh, 2004). The Fung-Hsieh 7-factor model can be expressed as:

$$\begin{aligned} R_{it} = \alpha_i &+ \beta_i^{SPCOMP} SPCOMP_t + \beta_i^{SCMLC} SCMLC_t + \beta_i^{BD10RET} BD10RET_t \\ &+ \beta_i^{BAAMTSY} BAAMTSY_t + \beta_i^{PTFSBD} PTFSBD_t + \beta_i^{PTFSFX} PTFSFX_t \\ &+ \beta_i^{PTFSCOM} PTFSCOM_t + \varepsilon_{it}, \end{aligned} \tag{4}$$

where $SPCOMP_t$ = equity market factor at time t, $SCMLC_t$ = size spread factor at time t, $BD10RET_t$ = bond market factor at time t, $BAAMTSY_t$ = credit spread factor at time t, $PTFSBD_t$ = bond trend-following factor at time t, $PTFSFX_t$ = currency trend-following factor at time t, $PTFSCOM_t$ = commodity trend-following factor at time t, β_i^{θ} = fund i's factor exposure to θ, and θ = respective risk factors in the model.

Fung-Hsieh 9-factor model

Later, Fung and Hsieh added two more trend-following factors to the original 7-factor model. These two factors represent the returns of a fund making bets on volatility in the interest rate and stock market (Fung & Hsieh, 2004). The regression equation for the extended model is:

$$\begin{aligned} R_{it} = \alpha_i &+ \beta_i^{SPCOMP} SPCOMP_t + \beta_i^{SCMLC} SCMLC_t + \beta_i^{BD10RET} BD10RET_t \\ &+ \beta_i^{BAAMTSY} BAAMTSY_t + \beta_i^{PTFSBD} PTFSBD_t + \beta_i^{PTFSFX} PTFSFX_t \\ &+ \beta_i^{PTFSCOM} PTFSCOM_t + \beta_i^{PTFSIR} PTFSIR_t + \beta_i^{PTFSSTK} PTFSSTK_t \\ &+ \varepsilon_{it}, \end{aligned} \tag{5}$$

where $PTFSIR_t$ = interest rate trend-following factor at time t, $PTFSSTK_t$ = stock trend-following factor at time t, β_i^{θ} = fund i's factor exposure to θ, and θ = respective risk factors in the model.

5.1.2 Return Unsmoothing

To obtain the real returns of hedge funds, we apply Brooks and Kats' (2002) method of return unsmoothing. Brooks and Kats' method is based on Geltner's (1993) method to deal with the real estate markets. Due to smoothing in appraisals and infrequent valuations of properties, the returns of real estate investments face similar problems as hedge fund returns, that is, autocorrelation (Brooks & Kat, 2002). We apply Brooks and Kats' (2002) method to unsmooth the reported returns in our database. The reason why we use Brooks and Kats' method is that our greatest concern relates to reported returns in the previous period, and Brooks and Kats' method is specifically designed to correct for autocorrelation of order 1.

According to Brooks and Kats' method, the observed return of a fund in period *t* is based on the return in the previous period *t-1*. Hence, the observed return of a fund in period *t* (R_t^O) is considered to be a weighted average of its "true" return at time *t* (R_t^C) and the observed return at time *t-1* (R_{t-1}^O). The observed returns can be considered as an autoregressive model of order 1 [AR(1)]:

$$R_t^O = (1-c)R_t^C + cR_{t-1}^O, \tag{6}$$

where c is a weighted coefficient in period *t.* Expression (6) can easily be reorganized to express the unsmoothed "true" return of a fund in period *t*:

$$R_t^C = \frac{R_t^O - cR_{t-1}^O}{(1-c)}, \tag{7}$$

where c can be interpreted as the autocorrelation coefficient of the first order (p) in period t:

$$R_t^C = \frac{R_t^O - cR_{t-1}^O}{(1-p)}. \tag{8}$$

By performing this procedure for all hedge funds in our sample we obtain a new time series of "true" returns. According to Brooks and Kat (2002), the adjusted returns will be free of autocorrelation and have the same mean as the observed returns, but a higher variance.

5.1.3 Rolling Window Regression

Hedge fund managers can quickly adjust their portfolios if the market conditions change. As a result, the portfolios' exposure to the various risk factors change. Therefore, hedge funds' exposure to risk factors are considered to be dynamic and time-varying. As linear factor models assume constant factor exposure, the coefficient estimates can be unstable and biased if we apply linear factor models on time-varying risk factors. To avoid this problem, we use a rolling window regression to allow for time-varying factor exposure (Shin, Smolarski & Soydemir, 2018). To determine whether or not we should use a rolling window regression, we employ Shin, Smolarski, and Soydemirs' (2018) test for time-varying factor exposure. The test is well-recognized and widely used in the literature.

To test if hedge funds exhibit time-varying factor exposure to risk factors we employ Shin, Smolarski, and Soydemirs' (2018) stability test of rolling window betas. To test hedge funds' factor exposure, we run a 24-month rolling window regression on each risk factor to obtain its corresponding coefficients (β_{iT}). The coefficients from the rolling regressions represent the factor exposures for each 24-month window, and we define the first 24-month as T=1, the next 24-month as T=2, and so on (Shin, Smolarski & Soydemir, 2018). To test whether the estimated coefficients are constant, we apply the following regression model:

$$\beta_{iT} = \gamma_i + T + T^2 + \vartheta_{iT}, \tag{9}$$

where β_{iT} = fund i's risk factor coefficient at sequence T, γ_i = constant term of fund i, T = sequence of windows and ϑ_{iT} = error term of fund i at sequence T.

By running regression (9) for all risk factors, we obtain estimates of the coefficients for T and T^2. If the estimates of T and/or T^2 are significantly different from zero, the fund exhibit time-varying factor exposure. Then a rolling window regression should be used, to allow for time-varying factor exposure. If the estimates of T and T^2 are not significantly different from zero, then the funds exhibit constant factor exposure over time. Hence, traditional linear factor models can be used to assess hedge fund performance.

5.2 Measurement of Skill

In the literature, managerial skill is usually thought to be manifested in the gross alpha, where a positive alpha signals managerial skill. However, as Berk and Binsbergen (2015) argue, the alpha can be a misleading measure of managerial skill.[1] Instead, they propose to use the value mutual fund managers extract from financial markets as a measure of managerial skill, which they term the value added. We consider the argumentation provided by Berk and Binsbergen to be applicable to the hedge fund industry as well as the mutual fund industry.

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[1] See Section 2.2.1 for Berk and Binsbergens' arguments on why the alpha may not be an appropriate measure of managerial skill.

As mentioned, most research uses the alpha as measure of managerial skill in the hedge fund industry. Generally, the alpha is used as a measure of performance and is usually calculated by comparing the performance of an investment to the second-best investment opportunity. In this context, the alpha can be perceived as a relative measure of managerial skill. As hedge funds aim for absolute returns and not relative returns, we find it more appropriate to use an absolute measure of skill rather than a relative measure. Thus, we consider the value added to be a better measure of managerial skill than the traditional alpha as the value added can be perceived as an absolute measure.

Another argument for using value added as a measure of managerial skill is related to fund size (AUM). We expect that if a hedge fund performs well, investors will find it attractive to invest in the fund and the fund size will increase. As the hedge fund size increases, the alpha can potentially decrease due to diseconomies of scale (Liang & Schwarz, 2011). Another potential consequence of an increase in the fund size is that hedge fund managers cannot utilize the same investment strategies for a greater amount of capital. As a result, hedge fund managers have to explore new investment opportunities that are less profitable when the fund size increase, causing the alpha to decrease. If alpha decreases with fund size, managerial skill will decrease accordingly if alpha is used as the measure of managerial skill. We find this counterintuitive as we would expect the most skilled managers to attract the most capital, so that the most skilled managers would control the largest hedge funds. Therefore, we consider the value added to be a better measure of managerial skill as it takes fund size into account.

In the following sections, we present how we estimate the value added and how we test for persistence in the value added estimates.

5.2.1 Value Added

We use the value hedge fund managers extract from financial markets as our measure of managerial skill, which is referred to as the value added. The value added measure was first introduced by Berk and Binsbergen (2015), who used the measure to study managerial skill in the mutual fund industry.

To obtain the realized value added from one period to the next, we multiply the individual alpha estimate ($\alpha_{i,t}$) from the factor model by the size of the fund at the end of the previous period ($AUM_{i,t-1}$). The monthly value added estimate for fund i in period t can then be described as:

$$V_{it} = \alpha_{i,t} \times AUM_{i,t-1}. \tag{10}$$

Our measure of managerial skill equals the expectation of (10):

$$S_i = E[V_{it}]. \tag{11}$$

The value added estimate for an individual hedge fund is given by the sum of the fund's value added numbers (V_{it}), divided by the number of periods the fund appears in our database (T_i):

$$\hat{S}_i = \sum_{t=1}^{T_i} \frac{V_{it}}{T_i}. \tag{12}$$

To obtain the aggregate value added for all the hedge funds in our database, we estimate the average value added across all hedge funds. There are two ways to do this. The first approach, the ex-ante approach, measures the mean of the distribution of which the value added is drawn. By using the ex-ante approach, the estimated mean is given by the sum of the average value added estimates ($\hat{S}_i$) for all hedge funds in our sample divided by the number of funds in our database (N):

$$\bar{S} = \frac{1}{N} \sum_{t=1}^{N} \hat{S}_i. \tag{13}$$

The second approach, the ex-post approach, emphasizes the total number of observations, rather than the number of hedge funds. By weighting each hedge fund by the number of periods it appears in our database (T_i), the estimated mean is given by:

$$\bar{S}_W = \frac{\sum_{t=1}^{N} T_i \hat{S}_i}{\sum_{t=1}^{N} T_i}. \tag{14}$$

The ex-ante and ex-post approach differ in how they estimate the average value added across hedge funds and there is no clear answer regarding which method to use.

5.2.2 Persistence

The average value added across hedge funds indicates whether the overall hedge fund industry is generating value, but it does not reveal whether or not the value generation is due to luck or skill. To separate skill from luck, we test the persistence of the value added estimates. We employ two methods to test for persistence. The first method is based on t-statistics and the second is a nonparametric method. Both tests are based on the skill ratio defined by Berk and Binsbergen (2015). The aim of the skill ratio is to separate lucky managers, who have generated a couple of high value added numbers, from skilled managers who consistently perform well. The skill ratio is defined as the time-weighted average value added ($\hat{S}_i^T$) divided by the corresponding standard deviation [$\sigma(\hat{S}_i^T)$] at time T:

$$SKR_i^T = \frac{\hat{S}_i^T}{\sigma(\hat{S}_i^T)}, \tag{15}$$

where:

$$\hat{S}_i^T = \sum_{t=1}^{T} \frac{V_{it}}{T} \quad \text{and} \quad \sigma(\hat{S}_i^p) = \frac{\sqrt{\sum_{t=1}^{T}(V_{it} - \hat{S}_i^T)^2}}{T}. \tag{16}$$

The skill ratio is essentially the t-statistic of the value added estimate for a specified period of time. The higher the skill ratio, the more skilled the hedge fund manager is, and the opposite applies to lower values.

Persistence Test Based on t-statistics

To test for persistence among Nordic hedge funds we use a method based on t-statistics. The test allows us to investigate managerial skill for different deciles based on hedge fund managers' performance. The purpose of the test is to examine which hedge fund managers that possess managerial skill. In addition, the method allows us to examine variations in the value added generated by the different hedge fund deciles over time.

We start by sorting all hedge funds into deciles based on their skill ratio for a specified time period, referred to as the sorting period. After the hedge funds are sorted into deciles, we estimate the average monthly value added for each decile for various measurement horizons, ranging from three to ten years. Then we perform a t-test to determine whether the value added estimates are significantly different from zero. At the end, we are left with each decile's average monthly value added and a corresponding p-value for all the measurement horizons.

There are three potential outcomes of this method. First, if a manager generates a significant positive value added for all measurement horizons, we consider the manager to be in the possession of managerial skill. Secondly, if a manager generates a significant negative value added for all measurement horizons, we consider the manager to be unskilled. Thirdly, if the value added generated by a manager is insignificant for one or more of the measurements horizons, we cannot determine whether the manager is skilled. In addition, the method allows us to examine variation in the value added numbers over time. A value added that deviates from the trend, can be a result of luck. Hence, we cannot conclude whether variation in the value added numbers is solely a result of managerial skill.

Nonparametric Persistence Test

In addition to the persistence test based on t-statistics, we employ a nonparametric test for persistence due to potential econometric shortcomings of the first persistence test. The t-statistics can be overstated for two reasons. First, the value added estimates across hedge funds may be correlated, and secondly, the distribution of value added may feature excess kurtosis (Berk & Binsbergen, 2015). We use Agarwal and Naiks' (2000) nonparametric method to test for persistence in the value added estimates as this method does not face the same econometric shortcomings as the first test. The method is based on a two-period framework, comparing performance measures for sequential periods. Agarwal and Naik (2000) use alpha and appraisal ratio as their performance measures, we use Berk and Binsbergens' (2015) skill ratio as our performance measure. To increase the number of observations and the power of Agarwal and Naiks' method, we use overlapping time periods.

The nonparametric test is based on constructing a contingency table with classifications of winner and loser hedge funds. We classify a hedge fund as a winner if its skill ratio is greater than the median skill ratio for a specified time interval, and otherwise, we classify it as a loser. If a hedge fund has the same classification for two consecutive periods, either winner/winner (N_{WW}) or loser/loser (N_{LL}), we consider the hedge fund to be persistent in these periods. On the contrary, hedge funds having different classifications for two consecutive periods are considered not to be persistent and are denoted by N_{WL} or N_{LW}. After we have constructed the contingency table, we calculate the cross-product ratio (CPR) and chi-square statistic to test whether the value added estimates are persistent or not.

The cross-product ratio (CPR) is given by the ratio of the observations which shows persistence in performance against the ones that do not:

$$CPR = \frac{N_{WW} \times N_{LL}}{N_{WL} \times N_{LW}}. \tag{17}$$

Our null hypothesis is that CPR equals to 1, which represents lack of persistence in the hedge fund industry. To evaluate the CPR, we use the Z-statistic (Eling, 2008):

$$Z = \frac{ln(CPR)}{\sigma_{ln(CPR)}}, \tag{18}$$

where the denominator equals the standard error of the natural logarithm of CPR, given by:

$$\sigma_{ln(CPR)} = \sqrt{\frac{1}{N_{WW}} + \frac{1}{N_{WL}} + \frac{1}{N_{LW}} + \frac{1}{N_{LL}}}, \tag{19}$$

If the Z-statistic is greater than its critical value (1.96 at the 5% level), we reject the null hypothesis. Then the conclusion of the test is that the value added estimates are persistent and that managerial skill is present in the Nordic hedge fund industry.

The chi-square test is considered to be more robust than the CPR test if survivorship bias is present (Agarwal & Naik, 2000). The chi-square test compares the observed frequency distribution of N_{WW}, N_{WL}, N_{LW}, and N_{LL}, against the expected frequency distribution for each outcome. We compute the chi-square statistic as:

$$\chi^2 = \frac{(N_{WW} - D1)^2}{N} + \frac{(N_{WL} - D2)^2}{N} + \frac{(N_{LW} - D3)^2}{N} + \frac{(N_{LL} - D4)^2}{N}, \tag{20}$$

where:

$$D1 = \frac{(N_{WW} + N_{WL}) \times (N_{WW} + N_{LW})}{N}, D2 = \frac{(N_{WW} + N_{WL}) \times (N_{WL} + N_{LL})}{N}, \tag{21}$$

$$D3 = \frac{(N_{LW} + N_{LL}) \times (N_{WW} + N_{LW})}{N}, D4 = \frac{(N_{LW} + N_{LL}) \times (N_{WL} + N_{LL})}{N},$$

and N is the total number of classifications in our contingency table:

$$N = N_{ww} + N_{WL} + N_{LW} + N_{LL}. \tag{22}$$

For the chi-square test our null hypothesis is identical to the null hypothesis for the CPR test, i.e., lack of persistence. Following a chi-square distribution with one degree of freedom, we reject the null hypothesis if the chi-square statistic is greater than 3.84 at the 5% level and conclude that managerial skill is present in the hedge fund industry.

6. Data

In this section we describe the data we use to examine our three hypotheses. First, we describe how we collect and clean the hedge fund data, followed by some descriptive statistics. Secondly, we present the data sources to our risk factors and how we construct these risk factors. Last in this section, we present potential biases to our dataset.

6.1 Hedge Fund Data

To examine the Nordic hedge fund industry, we construct a unique database on operating hedge funds in the Nordics. To our knowledge, there are currently no other databases available with the relevant data for this paper. In the following we present how we collect the necessary data, what adjustments we perform and potential biases to our dataset.

6.1.1 Data Collection

The main data source of our paper is HedgeNordic (HedgeNordic, 2018). HedgeNordic is a website reporting news and information on the Nordic hedge funds industry. The website collects data on Nordic hedge funds, but since most Nordic hedge funds are relatively new and most of them are not required to disclose their fund information, there is limited historical data available on Nordic hedge funds.

From HedgeNordic we assemble data on 180 currently operating Nordic hedge funds. The data includes monthly observations of gross returns and assets under management (AUM). In addition, we collect general information for each individual hedge fund in our sample. The general information includes inception date, legal structure, fund domicile, minimum investment requirement, currency, management fee and performance fee. Although HedgeNordic provides performance data for 180 Nordic hedge funds, they only have AUM data for 70 hedge funds as of today. Since assets under management figures are important to our study, we only include hedge funds where we possess both performance and assets under management data.

6.1.2 Data Cleaning

We perform several data adjustments to convert the raw data collected to a proper database. The assets under management data for Nordic hedge funds is reported in different currencies. To make observations comparable, we convert all the assets under management figures to US dollar ($). The exchange rates were obtained 10/04/2018 from Norges Bank (Norges Bank, 2018). Further, to be able to compare our assets under management figures, we adjust for inflation. We use the Norwegian CPI-index as a proxy for inflation in the Nordics and we use August 2018 as the base month. Furthermore, as there has been an increasing number of hedge funds in the Nordics, the historical data of each hedge fund varies in length. A few hedge funds included in our database have inception dates going back as far as 1998. However, most of the hedge funds in our database were not operating in the 1990s and early 2000s. Therefore, to ensure a sufficient number of observations in each monthly time period and to increase the robustness of our analysis, we exclude all observations before January 2004.

To reduce a potential self-selection bias in our data we perform two adjustments. First, we remove all hedge funds with less than 12 months of data.[2] Secondly, we remove all hedge funds whose assets under management do not exceed $5 million at least once during their lifetime.

6.1.3 Descriptive Statistics

After completing the data cleaning process, 62 Nordic hedge funds are left in our database. The timespan of our data is from January 2004 to August 2018. The data consists of monthly data for return and assets under management. In addition, general information for all hedge funds are included in the database.

Descriptive Statistics of Hedge Fund Characteristics

Variable	Mean	P_{25}	Median	P_{75}	St. Dev	n
Size (in million $)	279.36	46.98	107.99	307.89	513.47	62
Age (in months)	113.31	68.00	113.50	163.00	49.56	62
Management fee	1.11%	1.00%	1.00%	1.50%	0.42%	62
Performance fee	15.58%	10.00%	20.00%	20.00%	6.50%	62
Min. investment (in million $)	1.12	0.05	0.10	0.50	3.37	45
High-water mark (YES=1)	0.87	1.00	1.00	1.00	0.34	62

Table 1:*The table presents descriptive statistics of hedge fund characteristics for our sample of 62 funds. The statistics are based on data for the time period Jan 2004 – Aug 2018 [HedgeNordic, 2018].*

Table 1 provides descriptive statistics of hedge fund characteristics for our full sample. As the table illustrates, the size of the hedge funds varies, and the average fund size is far greater than the median ($279 million vs. $108 million). We see that the average age of a Nordic hedge

[2] See Section 6.3 for explanation of self-selection bias.

fund exceeds nine years and that the standard deviation exceeds four years. Further, all hedge funds operate with both a management fee and a performance fee, where the latter is often related to a high-water mark. The average management and performance fee are 1.11% and 15.58% respectively, and there are relatively small variations in the management fees in the Nordics.

Correlation Matrix of Hedge Fund Characteristics

	Min. investment	Management fee	Performance fee	Age	High-water mark
Min. investment	1.0000				
Management fee	0.0429	1,0000			
Performance fee	0.0386	0.0674	1.0000		
Age (months)	0.3440	-0.0582	0.1467	1.0000	
High-water mark	0.0836	0.2708	0.6708	0.0857	1,0000

***Table 2**: The table presents the correlation between the various hedge fund characteristics for the 62 Nordic hedge funds. The statistics are based on data for the time period Jan 2004 – Aug 2018 [HedgeNordic, 2018].*

Table 2 presents the correlation matrix of the general hedge fund characteristics. At first glance, we observe that high-water mark and performance fee are highly correlated. We expect these two characteristics to be highly correlated because the high-water mark usually is imposed to regulate the performance fee payments to hedge fund managers. Next, we find fund age to be negatively correlated with management fee. The negative relationship indicates that the older the hedge fund is, the lower is the management fee. We also find age to be positively correlated with minimum investment, indicating that investor requirements increase with fund age. Finally, we find positive correlation between high-water mark and management fee, suggesting that the higher the management fee, the more likely the hedge fund it to impose a high-water mark.

Comparative Descriptive Statistics Between Sample and Population

Variable	Mean	P_{25}	Median	P_{75}	St. Dev	Skewness	Kurtosis	n
Population	0.51 %	-0.55 %	0.43 %	1.57 %	0.0291	-0.69	27.10	16 434
Sample	0.64 %	-0.46 %	0.55 %	1.90 %	0.0316	-1.68	34.43	7 025
Two-sample t-test for Differences in Mean:								
t-statistic	3.1377							
Degrees of freedom	23 457							

***Table 3**: The table illustrates descriptive statistics of monthly smoothed returns for our sample and population. The t-statistic is the test statistics from* an unpaired two-sample t-test for comparison of means. *The statistics are obtained for the time period January 2004 to August 2018,* and the critical value for the t-statistic is 1.96 at the 5% level *[HedgeNordic, 2018].*

In Table 3, monthly reported return data on the total population of Nordic hedge funds is compared to our sample. From the table, we notice that our sample has a slightly greater mean than the population. From the t-test we reject the null hypothesis of equal means for our sample and the population. Hence, we can conclude that the average return of our sample of 62 Nordic hedge funds is different from the average return of the total population of 180 Nordic hedge funds. Although the mean of our sample differs from the population, it does not imply that our sample is not representative for the Nordic hedge fund industry. All Nordic hedge funds have reported their returns, hence no Nordic hedge funds hide their performance by not reporting. Our sample is arguably random because it is selected based on the availability of assets under management data and not by the availability of return data. Furthermore, we see that other statistical properties, such as standard deviation, skewness and kurtosis, only exhibit minor differences between the sample and the population. Based on these findings, and the fact that the sample is arguably random, we conclude that our sample is representative for the Nordic hedge fund industry.[3]

6.2 Factor Data

To assess hedge fund performance, we apply linear factor models with various risk factors. Some of the risk factors are commonly used and can easily be obtained, while others need to be constructed. In the following, we describe how the data is obtained and how we construct the risk factors that we could not obtain directly from other data sources.

6.2.1 Data Collection

A part of our analysis includes estimating alphas with the use of linear factor models. Since Nordic hedge funds invest in a vast part of the world, they are exposed to risk factors worldwide. For that reason, we use US data for our risk factors due to the US financial market's global impact. Our database includes monthly data from January 2004 to August 2018 for all risk factors.

To construct the two equity factors in the Fung-Hsieh models we collect data from Datastream on the S&P 500 Index and the Russell 2000 Index (Datastream, 2018). In addition, we collect data on the MSCI Emerging Market Index from Datastream, where the data provided are used

[3] See Section 6.3 for random sample arguments.

directly for our emerging market factor (Datastream, 2018). For all three indices, we collect data on the first daily observation in each month.

From the US Federal Reserve’s website, we collect data on the 10-year US Treasury, Moody’s Seasoned Baa Corporate Bond Yield and the TED spread (Federal Reserve, 2018). We use the 10-year US Treasury and Moody’s Seasoned Baa Corporate Bond Yield to compute the fixed-income factors of the of Fung-Hsieh models, while the TED spread represents the TED factor directly. The Federal Reserve calculate the TED spread by taking the spread between the 3-month USD LIBOR and the 3-month Treasury Bill (Federal Reserve, 2018).

We obtain the data for the five trend-following factors of the Fung-Hsieh models directly from David A. Hsieh’s Hedge Fund Data Library (Hedge Fund Data Library, 2018). Next, we obtain data on all the factors in the Carhart 4-factor model directly from Kenneth R. French Data Library (French’s Data Library, 2018). Finally, we obtain data on the VIX factor directly from the Chicago Board Volatility Index on Yahoo Finance (Yahoo Finance, 2018).

6.2.2 Factor Construction

The two equity factors of the Fung-Hsieh models are constructed by calculating the monthly change in returns for the S&P 500 Index (equity market factor), and by subtracting the monthly change in the S&P 500 Index from the monthly change in the Russell 2000 Index (size spread factor). The two fixed-income factors of the Fung-Hsieh models are obtained by taking the monthly percentage point change in the 10-year US Treasury (bond market factor), and by subtracting the percentage point change in Moody’s Seasoned Baa Corporate Bond Yield from the 10-year US Treasury (credit spread factor).

6.3 Biases

Our database may suffer from biases. One potential bias is the self-selection bias, which originates from the lack of disclosure in the hedge fund industry. Most hedge funds are registered as private investment vehicles and are not required to disclose their fund information. As a result, reported hedge fund returns can potentially be skewed. Hedge funds with promising returns are more likely to disclose their fund information, causing a positive skew. Hedge funds that are sufficiently well-known or not looking for additional capital are less likely to report, causing a negative skew (Fung & Hsieh, 2001). The potential of both a positive and a negative skew, results in an unknown effect of self-selection bias to our data.

In our database, we do not have AUM data for all the Nordic hedge funds and the potential of a self-selection bias is present. However, HedgeNordic states that there have been no occurrences where hedge funds refuse to report their assets under management figures and that the selection is random (HedgeNordic, 2018). Based on the unknown effect of the self-selection bias and HedgeNordic's statement, we find it reasonable to assume that our data is not suffering from a self-selection bias. Consequently, we consider our sample to be random and representative for the Nordic hedge fund industry.

Another potential bias to our database, is the backfill bias. When a hedge fund decides to report to a database, it has the option to backfill its historical returns prior to the listing date. If the historical returns are poor, a manager will not want to backfill fund returns. On the contrary, if the historical returns are promising, the manager is likely to report them. As a result, there is a potential upward bias in the average reported returns. To adjust for the potential backfill bias, all hedge funds where the inception date does not equal the date of the first observation in our database are removed. However, we cannot be certain that the backfill bias is removed completely. Another way to reduce the potential backfill bias is to remove the first 24 months of observations for each fund (Agarwal, Bakshi & Huij, 2009). We choose not to remove the first 24 months of observations in our database for two reasons. First, we have already adjusted for the bias by removing hedge funds where the inception date is not equal to the date of the first observation of the fund. Secondly, by removing the first 24 months of data for each fund we would lose a large number of observations, resulting in less robust analyses.

Further, funds that have been reporting to a database for a while may suddenly encounter financial distress, or at some point, cease to exist. HedgeNordic removes hedge funds that no longer operate on a monthly basis. Consequently, our database only contains surviving hedge funds, i.e., funds that are operating as of August 2018. The removal of "dead" hedge funds can lead to a survivorship bias in our data because historical returns are being overestimated and risks are being underestimated (Fung & Hsieh, 2001). However, as we do not know the effect of the survivor bias on our database, we choose to neglect it for further analyses.

7. Analysis

With a focus on value added, we investigate whether or not hedge fund managers possess managerial skill. To estimate the value added, we use an extension of the Fung-Hsieh 7-factor model. Our research address three topics within the field of hedge fund performance. First, we identify whether the average hedge fund manager generates a positive value added on a monthly basis. Secondly, we address persistence in the value added estimates. Finally, we examine how value added is affected by general hedge fund characteristics.

7.1 Factor Models

As there is no consensus regarding a generally accepted factor model to assess hedge fund performance, we compare five factor models: CAPM, Fama-French 3-factor model, Carhart 4-factor model, and Fung-Hsieh 7-factor and 9-factor models.[4] All five models are regressed on the unsmoothed returns of the value weighted Nordic hedge fund market. The value weighted Nordic hedge fund market is constructed as a portfolio of all the hedge funds in our sample, by weighting each fund on their market share of the total Nordic hedge fund industry. Market share is measured as each fund's fraction of the total AUM in the Nordics as of August 2018.

The differences in the alpha estimates from the five factor models are relatively small and they are all significant at the 5% level. How well the different factor models explain hedge fund performance vary, but we see that the Fung-Hsieh 7-factor and 9-factor models provide the highest explanatory powers (R^2), of 22.3% and 22.9% respectively. The fact that the Fung-Hsieh models provide the highest explanatory powers is consistent with the research of Fung and Hsieh (1997), which states that traditional linear factor models have difficulties in explaining hedge fund performance because hedge funds exhibit non-linear exposures to standard asset classes. We also find that the CAPM has difficulties in explaining hedge fund performance, which is consistent with the study of Kazemi, Martin, and Schneeweis (2001). Based on the findings from the five regressions we conclude that hedge funds are not being market neutral.

[4] See Table 11 in Appendix for comparison of factor models.

As the number of significant variables in the model, the R^2 criterion, the Akaike information criterion (AIC), and the Bayesian information criterion (BIC) all favor the Fung-Hsieh 7-factor model, we proceed with this model for our stepwise regression analysis. We conduct a stepwise regression analysis to evaluate whether we can improve our 7-factor model by adding additional risk factors to the model. Using stepwise regression, we find that the aggregate volatility factor (VIX factor) is significantly related to hedge fund returns, which is consistent with the findings of Avramov, Barras, and Kosowski (2013). Since the VIX index increases as market uncertainty increases and investors are turning pessimistic, the VIX factor is inversely related to hedge fund performance. So, by trading options on the underlying assets of the VIX Index, Nordic hedge fund managers can potentially achieve diversification benefits and/or eliminate the skew and excess kurtosis that many hedge fund strategies exhibit (Black, 2006; Daigler & Rossi, 2006). As the inclusion of the VIX factor enhance the explanatory power of our model, and both the AIC and the BIC improve when adding the VIX factor to the model, we choose to add the VIX factor to the Fung-Hsieh 7-factor model.[5] Further analyses on value added are based on this 8-factor model.

Like Brooks and Kat (2002), we find evidence of autocorrelation in reported returns in the Nordic hedge fund industry.[6] To adjust for autocorrelation, we follow Brooks and Kats' method of return unsmoothing. As Nordic hedge funds also exhibit time-varying factor exposures, we apply a 24-month rolling window regression to allow for changes in hedge funds' factor exposures when estimating hedge fund alphas.[7]

7.2 Value Added

After estimating monthly alphas, we check for stationarity and compute average value added for each hedge fund.[8] Then we estimate the average value added across the hedge funds in our sample in two ways: by the use of the ex-ante distribution and ex-post distribution. The results are presented in Table 4.

[5] See Table 12 and 13 in Appendix for stepwise regressions.

[6] See Table 9 in Appendix for autocorrelation.

[7] See Table 10 in Appendix for stability test of rolling window betas, and Figure 1 and 2 for graphs of factor exposures.

[8] See Figure 3 in Appendix.

Value Added ($\hat{S}_i$)		
	Ex-ante	Ex-post
Cross-sectional mean	1.72	2.09
Standard error of the mean	0.34	0.06
t-statistic	5.02	35.46
1st Percentile	-0.37	-2.19
5th Percentile	-0.02	-0.33
10th Percentile	0.06	-0.05
25th Percentile	0.19	0.10
50th Percentile	0.50	0.52
75th Percentile	2.61	1.87
90th Percentile	5.34	6.15
95th Percentile	6.64	10.47
99th Percentile	14.07	24.73
Share greater than zero	93.55%	86.41%
No. of Funds	62	
No. of Observations	6 392	

***Table 4**: For all the hedge funds in our database, we estimate monthly value added, $\hat{S}_i$. The cross-sectional mean, standard error, t-statistic and percentiles are statistical properties of the distribution. The ex-ante statistics are based on the average value added per hedge fund and the total number of hedge funds in our sample. The ex-post statistics are based on monthly value added estimates and the total number of observations in our sample. For the ex-ante distribution share greater than zero is the fraction of hedge funds generating a positive average value added, and for the ex-post distribution it indicates the fraction of observations that are greater than zero. All numbers are reported in Y2018 million USD per month.*

We estimate the average monthly value added of Nordic hedge fund managers to be \$1.72 million (0.62% of avg. AUM) by using the ex-ante distribution, and \$2.09 million (0.75% of avg. AUM) by using the ex-post distribution. Both estimates are statistically significant, with t-statistics of 5.02 and 35.46 respectively. The positive value added indicates that Nordic hedge fund managers generate value on average. In the ex-post distribution, each observation is weighted equally. Hence, older hedge funds will have a greater effect than younger hedge funds on the ex-post mean. An ex-post mean greater than the ex-ante mean implies that the older hedge funds in our sample are performing better than the younger hedge funds on average. The standard error of the mean is greater for the ex-ante distribution (0.34) than the ex-post distribution (0.06).

From the percentiles we notice that there are differences in the average value added for the various percentiles. A negative value added is present around the 5th percentile under the ex-ante distribution and around the 10th percentile under the ex-post distribution. Although the lower percentiles generate a negative value added, we find that 93.55% of the Nordic hedge funds generate a positive value added on average, and that 86.41% of all monthly observations are positive. The median hedge fund manager generates a value added of $0.5 million (0.18% of avg. AUM) per month. Hence, the probability of observing a monthly value added less than the average is far greater than 50%. The fact that the median value added is smaller than the average implies that a few hedge funds contribute to the high average, causing our distribution to be skewed to the left.

Overall, the results indicate that the majority of operating Nordic hedge funds generate a positive monthly value added and this confirm our hypothesis of Nordic hedge fund managers generating a positive value added on average. Our results are consistent with Berk and Binsbergens' research on mutual funds and with previous literature finding positive alphas in the hedge fund industry.

7.3 Persistence

Although we find evidence of positive value added estimates for the Nordic hedge fund industry, our findings do not necessarily imply that Nordic hedge fund managers are skilled. To determine if Nordic hedge fund managers are skilled, we test for persistence in the value added estimates. We perform two different tests for persistence: one test based on t-statistics and one nonparametric test. As we have reason to believe that the t-statistics in the first test may be overstated due to econometric shortcomings, we conduct two persistence tests, where the second test does not assume a specific distribution.

7.3.1 Persistence Test Based on t-statistics

If a manager is skilled, we expect the manager to generate a positive value added consistently over time. To test managerial skill, we sort the hedge funds into deciles based on their skill ratio for the time period August 2008 to July 2011. Then we examine how the hedge funds in each decile perform for measurement horizons ranging from three to ten years. The hedge funds included in the first three years, the sorting period, are the hedge funds we study for all measurement horizons. Table 5 presents the average monthly value added and the corresponding p-value from the t-statistic for each of the deciles over seven different measurement horizons.

Persistence Test Based on t-statistics

Decile	Years	3	4	5	6	7	8	9	10
1st	Value added	-0.59	-0.29	0.05	0.67	1.84	2.31	2.13	2.32
	P-value	0.100	0.157	0.421	0.004	0.000	0.000	0.000	0.000
2nd	Value added	-0.23	-0.14	-0.08	-0.03	0.03	0.08	0.11	0.13
	P-value	0.215	0.264	0.323	0.429	0.401	0.232	0.118	0.064
3rd	Value added	2.69	2.51	2.89	3.14	3.14	3.02	2.82	2.65
	P-value	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000
4th	Value added	0.40	0.41	0.42	0.49	0.55	0.53	0.45	0.40
	P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
5th	Value added	0.66	0.64	0.71	0.76	0.75	0.70	0.66	0.65
	P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
6th	Value added	6.12	4.38	3.52	3.14	3.21	3.20	3.07	2.91
	P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
7th	Value added	5.47	6.12	6.70	7.30	7.19	6.86	6.70	6.41
	P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
8th	Value added	0.33	0.30	0.31	0.36	0.24	0.13	0.13	0.18
	P-value	0.000	0.000	0.000	0.000	0.000	0.024	0.016	0.001
9th	Value added	5.66	5.61	5.45	5.99	6.62	6.46	6.12	6.30
	P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
10th	Value added	2.98	2.69	2.55	2.64	3.03	3.18	2.90	2.73
	P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

***Table 5**: We sort the hedge funds in our database into 10 deciles based on their skill ratio for a three years sorting period (Aug 08-Jul 11). The average monthly value added (in million $) and the corresponding p-value (in decimals) from the t-statistic is presented for seven different measurement horizons, ranging from three to ten years. The value added numbers are inflation adjusted (Y2018). All horizons begin at August 2008, and the 10-year horizon ends on the most recent date in our database, August 2018. All the hedge funds in the different deciles are alive for the whole 10-year horizon.*

From Table 5, we notice that the bottom two deciles have a value added that is not significantly different from zero for several periods. Hence, the managers of the bottom two deciles are not persistently generating a positive value added, so we cannot conclude that these managers are in the possession of managerial skill. For the first horizons (3 to 5 years) the hedge fund managers in the 1st decile do not generate a value added significantly different from zero, which implies that they are unskilled. For the last horizons (more than 5 years) they generate a significantly positive value added, which implies that they are skilled. However, as the value added is not significant for all measurement horizons, we cannot conclude that the managers in the 1st decile are skilled. The managers in the 2nd decile generate a value added that is not significantly different from zero for all measurement horizons and we conclude that these managers are not in the possession of managerial skill.

The next three deciles, 3rd to 5th, have all a relatively stable average value added over the different measurement horizons. The hedge fund managers in these deciles generate a relatively small value added on average, except for the third decile. The value added generated in the 3rd to 5th deciles are significantly positive for all horizons. Hence, we consider the mangers in these deciles to be skilled. In addition, there is little variation in the value added numbers of the hedge fund managers in the 3rd to 5th deciles, which supports our conclusion that these managers are being skilled.

The 6th, 7th, and 9th deciles generate the highest value added numbers on average. A potential explanation of why the highest value added are generated by the hedge fund managers in these deciles, and not by the hedge funds in the 10th decile, is that their standard deviations are larger, hence their skill ratios are lower. As a result of higher standard deviations, we also observe higher variations in the average value added for these deciles. Further, as the hedge fund managers in the 6th, 7th, and 9th deciles generate a significant positive value added for all measurement horizons, we conclude that they are in the possession of managerial skill. The same conclusion applies to the 10th decile, which is also generating a significant positive value added for all measurement horizons.

From our persistence test based on t-statistics, we find that the top eight deciles of Nordic hedge fund managers are in the possession of managerial skill. For the two bottom deciles, we find no evidence of managerial skill. As a result, we find evidence of cross-sectional differences in managerial skill between the top and bottom managers in the Nordic hedge fund industry.

7.3.2 Nonparametric Persistence Test

Based on the findings in the previous section, it is tempting to conclude that the hedge fund managers in the 3rd to 10th deciles are skilled. However, as our t-statistics may be overstated, we also test for persistence using a nonparametric test.[9] Based on Agarwal and Naiks' (2000) method, we create a contingency table where we classify hedge funds as winners and losers in each period based on their skill ratio for a specified measurement interval. To examine whether persistence is sensitive to the number of observations we include in each period, we perform the test with three different measurement intervals: 3 months, 6 months, and 12 months. The frequency of the classifications and the corresponding CPR and chi-square statistics are presented in table 6.

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[9] See Section 5.2.2 for reasons why the t-statistics may be overstated.

Nonparametric Persistence Test

Interval	N_{WW}	N_{WL}	N_{LW}	N_{LL}	N	CPR	Z-statistic	Chi-square
12 months	135	65	70	134	404	3.98	6.54^{***}	44.50^{***}
6 months	166	81	82	169	498	4.22	7.54^{***}	59.40^{***}
3 months	195	72	74	196	537	7.17	10.16^{***}	111.79^{***}

Table 6*: The contingency table displays the number of times the hedge funds in our database are classified as winners or losers. We classify a fund as a winner if its skill ratio is greater than the median skill ratio for a specified time interval, and otherwise, we classify it as a loser. Then we study how hedge funds perform for two consecutive periods and present the frequencies of the outcomes. The results of the four possible outcomes are presented as Win/Win (N_{WW}), Win/Lose (N_{WL}), Lose/Win (N_{LW}) and Lose/Lose (N_{LL}). The CPR, Z-statistic and Chi-square are statistical properties of the distribution. The test is based on data from Jan 04 - Aug 18, and we operate with three different measurement intervals: 3 months, 6 months and 12 months. The critical value for the Z-statistic of the CPR is 2.58 and the critical value of the Chi-square-statistic is 6.63 at the 1% level. ***p<0.01, **p<0.05 and *p<0.1.*

Based on the results presented in Table 6, we can confirm our hypothesis of persistence in value added for all the three intervals. Both the Z-statistics and the Chi-square statistics are significant at the 1% level for all three intervals. The fact that the statistics are significant for all intervals indicates that the persistence is not sensitive to the number of monthly observations we include in the measurement interval. The results show that the value added numbers generated by Nordic hedge fund managers are persistent and that managerial skill is present in the Nordic hedge fund industry.

In addition to the CPR test, we conduct a Chi-square test, which is more robust to survivorship bias. As the conclusion from the chi-square test corresponds to the conclusion from the CRP test, a potential survivorship bias is not changing our conclusion. Furthermore, both the CPR and Chi-square statistics show the same trend of larger statistical values for shorter intervals. In addition, the CPR for the 3-month interval is almost twice as large as for the 12-month interval. The difference in the CPR implies that short-term persistence is present in a greater extent than long-term persistence. However, with significance at the 1% level for all intervals, we cannot conclude that persistence is more of a short-term phenomenon.

The results from both the persistence tests indicate that managerial skill is present in the Nordic hedge fund industry, which confirms our second hypothesis. From the persistence test based on t-statistics, we can conclude that the managers in the top eight deciles are skilled, but we do not find evidence of managerial skill in the bottom two deciles. As a result, we find cross-sectional differences in managerial skill between the top and bottom managers. From the nonparametric persistence test, we conclude that managerial skill is present in the Nordic hedge fund industry.

7.4 Fund Characteristics

To assess whether the value added solely can be attributed to managerial skill, or if parts of the value added can be explained by fund characteristics, we examine the relationship between value added and general hedge fund characteristics. To examine the relationship, we regress our monthly value added estimates on general fund characteristics using univariate and multivariate regressions. The characteristics we examine are minimum investment requirements, management fee, performance fee, fund age and if the hedge fund has a high-water mark. All the characteristics are utilized as constant variables. We hypothesize that none of the general fund characteristics will have a significant impact on the value added, i.e., if all hedge fund managers have the same level of managerial skill, differences in general characteristics will not influence the size of the value added.

Regressions of Hedge Fund Characteristics

	(1) Ln_VA	(2) Ln_VA	(3) Ln_VA	(4) Ln_VA	(5) Ln_VA	(6) Ln_VA
Min.investment	2.18e-08**					-4.08e-08***
	(7.92e-09)					(8.50e-09)
Management fee		-0.138*				-0.243***
		(0.0567)				(0.0590)
Performance fee			0.0182***			-0.0607***
			(0.00415)			(0.00639)
Age (months)				0.000300***		0.000277***
				(0.0000140)		(0.0000165)
High-water mark					0.687***	1.511***
					(0.0805)	(0.126)
Constant	6.410***	6.692***	6.229***	5.220***	5.921***	5.203***
	(0.0254)	(0.0667)	(0.0749)	(0.0658)	(0.0764)	(0.111)
No. of obs.	5 115	5 517	5 517	5 517	5 517	5 115
R^2	0.00	0.00	0.00	0.08	0.01	0.07

***Table 7**: The log of monthly value added (Ln_VA) is regressed on the five hedge fund characteristics displayed in the first column. Column (1) to (5) display univariate regressions and column (6) displays a multivariate regression. Standard errors are reported in parentheses. *p<0.10, **p<0.05 and ***p<0.01.*

From Table 7, several observations can be made. First, the effect of having a minimum investment requirement is unknown. In the multivariate regression, the minimum investment coefficient is negative, whereas it is positive in the univariate regression. The coefficients from both regressions are small, and we conclude that minimum investment requirements have a relatively small effect on the value added generated by Nordic hedge fund managers.

Secondly, our results show that Nordic hedge funds cannot justify a high management fee. The management fee coefficient is negative and has a relatively large effect on value added in both the univariate and the multivariate regression. One potential reason for the large effect of the management fee on the value added is that the fee is stated in percentage points. Further, there are relatively small variations in the management fees of the Nordic hedge funds and the average Nordic management fee is 1.11%. We estimate a one percentage point increase in the management fee to decrease the average monthly value added with 13.8% according to our univariate regression and with 24.3% when controlling for other fund characteristics as well (multivariate regression). A potential reason for why the management fee has a negative effect on hedge fund performance is that investors are sensitive to the fee size, so that a change in the fee can lead investors toward other hedge funds or alternative investment vehicles. Further, we find the performance fee to have an unknown effect on the value added, which is consistent to previous research on hedge fund characteristics.

Thirdly, we see that hedge funds that use a high-water mark as a part of their incentive structure perform better than those without it. One potential reason for the positive relation, is that a high-water mark aligns the incentives of hedge fund managers and investors. A high-water mark prevents hedge fund managers from excessive risk-taking, and investors might find this attractive as they prefer low risk hedge funds compared to high risk funds. Hence, a high-water mark can result in additional investments from investors, causing a potential higher value added. Consequently, hedge funds with a high-water mark perform significantly better than those without it.

Fourthly, older hedge funds tend to generate a high value added. In both regressions, the coefficient of fund age is significant at the 1% level. However, the coefficients are small. Our estimates suggest that for a one month increase in fund age the value added increases by 0.03%, all else equal. A potential explanation of the positive effect of fund age on value added is that managers of older hedge funds are more experienced than the managers of younger hedge funds.

Overall, the results show that part of the value added generated by Nordic hedge fund managers can be attributed to general hedge fund characteristics. Hence, we reject our third hypothesis, which states that the value added cannot be attributed to hedge fund characteristics. However, we see from Table 7 that all the regressions have low explanatory powers. Based on the explanatory powers, we conclude that general hedge fund characteristics only explain a small part of the variation in the value added generated by Nordic hedge fund managers. The results from the regressions indicate that hedge funds with certain characteristics are performing better than others for a given level of managerial skill. Nevertheless, based on the hedge fund characteristics' low explanatory powers the results do not change our conclusion from the previous parts, that managerial skill is present in the Nordic hedge fund industry. The results suggest that the value added generated by Nordic hedge fund managers is not solely a result of managerial skill, but that parts of the value added can be attributed to hedge fund characteristics.

8. Conclusion

In this thesis, we investigate managerial skill in the Nordic hedge fund industry from January 2004 to August 2018. To investigate whether Nordic hedge fund managers possess skills, we examine the value added generated by Nordic hedge fund managers, persistence in the value added numbers, and if general hedge fund characteristics can be attributed to the value added.

We find that the average Nordic hedge fund manager generates a positive value added of approximately \$2 million (0.72% of avg. AUM) per month, while the median manager generates \$0.5 million (0.18% of avg. AUM) per month. However, as a positive value added is not necessarily a result of managerial skill, we test for persistency in the value added estimates. The results from our two persistence tests confirm that managerial skill is present in the Nordic hedge fund industry. From the persistence test based on t-statistics, we conclude that the managers in the top eight deciles are skilled, but we do not find evidence of managerial skill in the bottom two deciles. As a result, there is evidence of cross-sectional differences in managerial skill between the top and bottom managers in the Nordic hedge fund industry. From the nonparametric persistence test, we conclude that managerial skill is present in the Nordic hedge fund industry. The result is not sensitive to the number of observations we include in our measurement interval.

To examine whether the value added generated by Nordic hedge fund managers can be attributed to other factors than managerial skill, we investigate the relationship between the value added and general hedge fund characteristics. First, we find that older, more experienced, hedge funds tend to generate a higher value added than younger funds. Secondly, we find Nordic hedge fund managers cannot justify a high management fee. Thirdly, we find that hedge funds imposing a high-water mark generate a higher value added than those without. Overall, the results show that parts of the value added can be attributed to general hedge fund characteristics. However, as the general hedge fund characteristics only can explain small parts of the variation in the value added, the results do not change our conclusion regarding Nordic hedge fund managers being skilled. The results suggest that the value added generated by Nordic hedge fund managers is not solely a result of managerial skill, but that parts of the value added can be attributed to hedge fund characteristics.

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Appendix

Hedge funds

Table 8 presents a list of the hedge funds in our database after the data has been cleaned. In total the list consists of 62 Nordic hedge funds of varying age and size. The Nordic countries include Norway, Sweden, Denmark, Finland and Iceland.

List of Hedge Funds in our Database

Hedge fund	Hedge Fund
AAM Absolute Return Fund Class B	Formuepleje Penta
Accendo Capital SICAV, SIF	Formuepleje Safe
Adrigo Fund	FX Alpha
Ambrosia L	Gladiator Fond
Arcturus A	HCP Black Fund
Asgard Credit Fund	HCP Focus Fund
Asgard Fixed income Fund	HCP Quant
Asymmetric – Global Macro Fund	HP Hedge
Atlant Edge	Inside Hedge
Atlant Opportunity	IPM Systematic Currency Fund
Atlant Sharp	IPM Systematic Macro Fund
Atlant Stability Offensiv	KLP Alfa Global Energi
Atlant Stability	KLP Alfa Global Rente
Bodenholm	Lynx (Sweden)
Borea European Credit	Midgard Fixed Income Fund
Borea Global Equities	Nektar
Brummer Multi-Strategy	Nordkinn Fixed Income Macro Fund
Capital Four Credit Opportunities Fund	Nykredit EVIRA Hedge Fund
Carnegie WorldWide Long/Short Fund	Nykredit KOBRA Hedge Fund
Catella Hedgefond	Nykredit MIRA Hedge Fund
Catella Nordic Corporate Bond Flex	Origo Quest 1(Class A)
Catella Nordic Long Short Equity	Pareto Nordic Omega
Crescit	PriorNilsson Idea
Danske Invest Hedge Fixed Income	PriorNilsson Yield
Elementa	Ress Life Investments
Estlander & Partners Alpha Trend program	Rhenman Healthcare Equity L/S IC1
Excalibur	SEB Asset Selection Opportunistic
Formuepleje Epikur	SEB Asset Selection
Formuepleje Fokus	Sector Zen Fund
Formuepleje Merkur	VISIO Allocator Fund
Formuepleje Pareto	WH Index

Table 8*: List of the 62 Nordic hedge funds in our database [HedgeNordic].*

Autocorrelation

Table 9 presents the autocorrelation coefficients for the 62 hedge funds in our sample. From the table it follows that 23 out of 62 hedge funds exhibit autocorrelation of order 1 (44% of the sample). The statistical significance of the autocorrelation is relative strong since 61% (14 out of 23 autocorrelated funds) of the coefficients are significant at the 1% level. Based on the evidence of autocorrelation there is reason to believe that the reported returns of the hedge funds in our database are smoothed. Consequently, we should unsmooth the reported returns to reduce the autocorrelation in our data.

Autocorrelation of First and Second Order for Smoothed Returns

Hedge fund	P_1		P_2		Hedge Fund	P_1		P_2	
AAM Absolute Return Fund Class B	0.0756		0.0449		Formuepleje Penta	0.1033		-0.076	
Accendo Capital SICAV. SIF	-0.071		-0.092		Formuepleje Safe	-0.04		-0.245	***
Adrigo Fund	0.1539	*	0.0154		FX Alpha	0.0691		0.240	*
Ambrosia L	0.0939		-0.205		Gladiator Fond	-0.069		-0.102	
Arcturus A	-0.084		0.1357		HCP Black Fund	0.1613	*	0.101	
Asgard Credit Fund	-0.047		-0.252		HCP Focus Fund	-0.152		-0.180	
Asgard Fixed income Fund	0.3912	***	0.0881	***	HCP Quant	0.1964		-0.065	
Asymmetric – Global Macro Fund	0.0582		-0.01		HP Hedge	0.4693	***	-0.069	***
Atlant Edge	0.2106	***	0.0326	**	Inside Hedge	0.015		-0.156	
Atlant Opportunity	0.0563		0.0985		IPM Systematic Currency Fund	0.0395		-0.065	
Atlant Sharp	0.3047	***	0.0924	***	IPM Systematic Macro Fund	-0.109		-0.055	
Atlant Stability Offensiv	0.2486	***	0.0534	***	KLP Alfa Global Energi	0.0422		0.1322	
Atlant Stability	0.4877	***	-0.21	***	KLP Alfa Global Rente	-0.079		0.1277	
Bodenholm	-0.092		0.0058		Lynx (Sweden)	-0.139	*	0.0033	
Borea European Credit	0.3074	***	-0.063	**	Midgard Fixed Income Fund	0.2164	**	-0.079	*
Borea Global Equities	-0.054		0.0306		Nektar	0.1505	**	0.1509	**
Brummer Multi-Strategy	-0.006		-0.085		Nordkinn Fixed Income Macro Fund	-0.168		-0.163	
Capital Four Credit Opportunities Fund	0.2194	**	0.1184	**	Nykredit EVIRA Hedge Fund	-0.349		-0.654	
Carnegie WorldWide Long/Short Fund	0.0906		0.1221		Nykredit KOBRA Hedge Fund	0.3377	***	-0.069	***
Catella Hedgefond	0.2184	***	0.0166	**	Nykredit MIRA Hedge Fund	-0.035		0.0443	
Catella Nordic Corporate Bond Flex	0.3247	***	-0.103	***	Origo Quest 1(Class A)	-0.081		-0.168	
Catella Nordic Long Short Equity	-0.054		0.0787		Pareto Nordic Omega	0.269	***	0.1432	***
Crescit	-0.158		-0.241	*	PriorNilsson Idea	0.1418	*	-0.101	
Danske Invest Hedge Fixed Income	0.2529	***	0.1188	***	PriorNilsson Yield	0.0218		0.018	
Elementa	0.2779	*	0.0766		Ress Life Investments	0.1364		0.0924	
Estlander & Partners Alpha Trend program	-0.003		-6E-04		Rhenman Healthcare Equity L/S IC1	0.0163		0.0479	
Excalibur	0.1212		0.167	**	SEB Asset Selection Opportunistic	-0.197	**	0.0509	*
Formuepleje Epikur	-0.01		-0.203		SEB Asset Selection	-0.029		0.0331	
Formuepleje Fokus	-0.081		0.1836		Sector Zen Fund	0.2395	***	-0.065	**
Formuepleje Merkur	-0.089		-0.131		VISIO Allocator Fund	0.0691		-0.089	
Formuepleje Pareto	-0.002		-0.263		WH Index	0.2223	***	-0.07	**

***Table 9**: The table presents the autocorrelation coefficients of order one (P_1) and two (P_2) for all the hedge funds in our sample. All coefficients marked with a star have significant autocorrelation of order one or two, where *p<0.05, **p<0.01 and ***p<0.001.*

Rolling Window Regression

Table 10 presents the results from the regression analysis of the coefficients in the extended Fung-Hsieh 7-factor model regressed against time *T*. 5 out of 8 risk factors exhibit linear relationships across time, and 4 out of 8 risk factors exhibit quadratic relationships across time. Although all the coefficients are quite low, only two of the risk factors are insignificantly related to both *T* and T^2. As the other six risk factors have at least one coefficient that is statistically significant different from zero, they all show a significant pattern over time. Therefore, we consider the coefficients of these factors to be unstable over time, i.e., time-varying. An alternative way to examine the time effect on risk exposures is by studying the graphs in Figure 1 and 2. From the graphs it seems like 5 or 6 out of 8 risk factors are time-varying, and that confirms our findings from the stability test. Hence, to adjust for the factor time-varying exposures we should use a 24-month rolling window regression for our analyses.

Stability Test of Rolling Window Betas

	(1) SPCOMP	(2) SCMLC	(3) BD10RET	(4) BAAMTSY	(5) PTFSBD	(6) PTFSFX	(7) PTFSCOM	(8) VIX
T	-.00138	.00139	-.039***	-.0343	-.000459**	-.00053***	.00036***	.000280**
	(.00100)	(.000871)	(.0127)	(.0248)	(.000183)	(.000166)	(.000132)	(.000116)
T^2	.0000049	-.000007*	0.000054	-.00002	0.000002**	.0000021**	-.00000***	-.000000611
	(.0000491)	(.00000427)	(.000623)	(.000122)	(.00000900)	(.00000814)	(.00000648)	(.00000568)
Constant	.173***	-.0141	1.824***	3.087***	.0352***	.0469***	-.00702	-.0451***
	(.0448)	(.0390)	(.570)	(1.113)	(.00822)	(.00744)	(.00592)	(.00518)
Observations	153	153	153	153	153	153	153	153
R^2	0.033	0.026	0.466	0.289	0.054	0.114	0.048	0.252

***Table 10**:The table reports the results from a stability test of each risk factor in our extended Fung-Hsieh 7-factor model. The test results are obtained by regressing the 153 beta estimates (β_{iT}) for each risk factor from the rolling window regressions on the sequence of 24-month windows. Standard errors are presented in parentheses, where *p<0.05, **p<0.01 and ***p <0.001.*

Time-varying Coefficients (a)

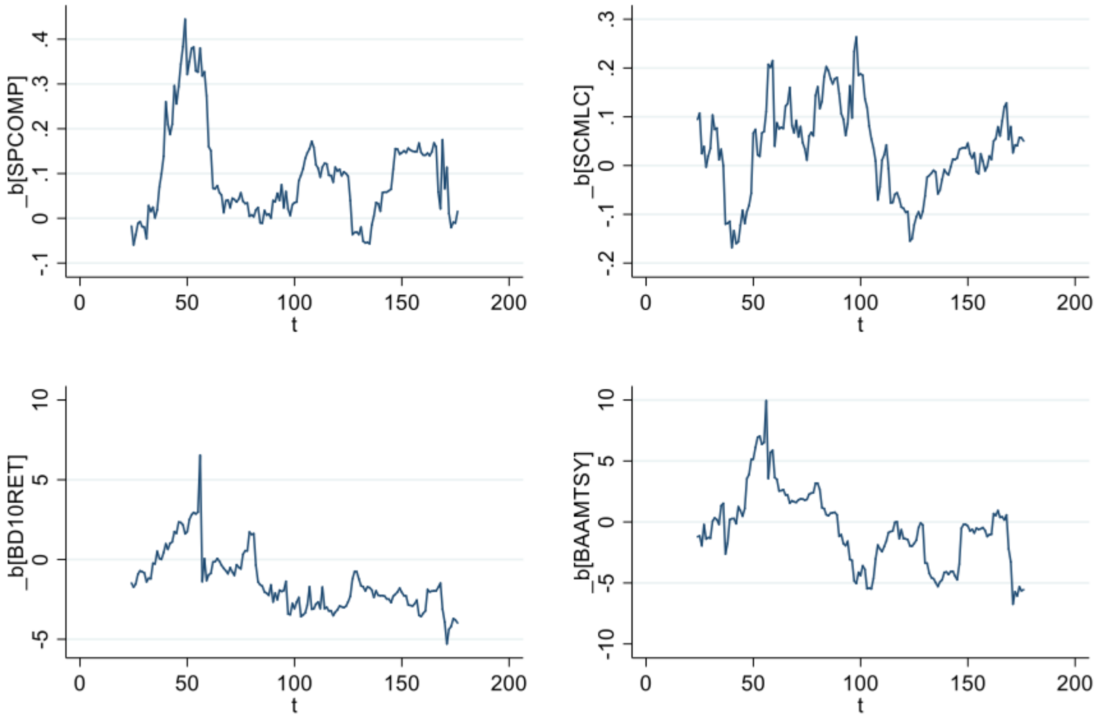

***Figure 1**: The graphs illustrate how actively Nordic hedge funds change their risk exposure to a risk factor. The first coefficient of the 24-month rolling regression is recorded on December 2005, and it represents the factor exposure of the sample period from January 2004 to December 1995. Then the next coefficient is computed by moving the fixed window one month ahead. The upper left graph shows the trend in the equity market factor (SPCOMP), the upper right graph the trend in the size spread factor (SCLMC), the lower left graph the trend in the bond market factor (BD10RET) and the lower right graph the trend in the credit spread factor (BAAMTSY). The graphs are based on data for Jan 04 - Aug 18.*

Time-varying Coefficients (b)

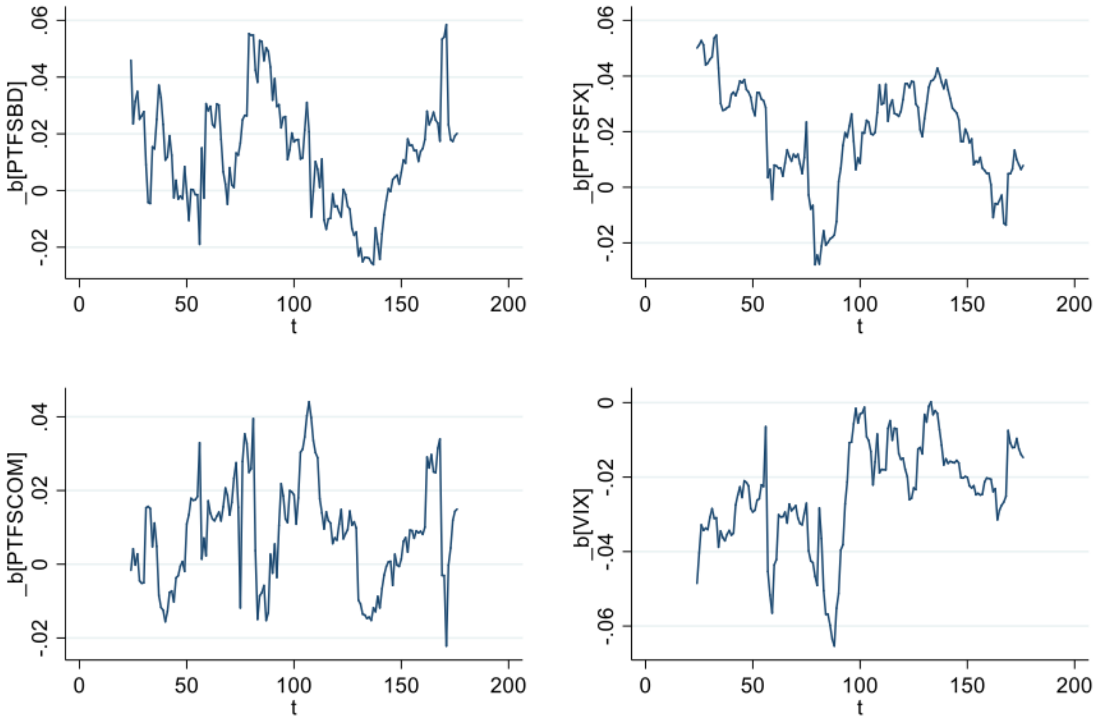

Figure 2*: The graphs illustrate how actively Nordic hedge funds change their risk exposure to a risk factor. The first coefficient of the 24-month rolling regression is recorded on December 2005, and it represents the factor exposure of the sample period from January 2004 to December 1995. Then the next coefficient is computed by moving the fixed window one month ahead. The upper left graph shows the trend in the bond trend-following factor (PTFSBD), the upper right graph the trend currency trend-following factor (PTFSFX), the lower left graph the trend in the commodity trend-following factor (PTFSCOM) and the lower right graph the trend in the volatility factor (VIX). The graphs are based on data for Jan 04-Aug 18.*

Stationarity

Before the average value added [$\hat{S}_i$] can be estimated for each hedge fund in our sample we have to check for stationarity. We check for stationarity because value added is computed by taking the product of the alpha and fund size (AUM), and these components are potentially not stationary due to trends, cycles, random walks or a combination of the three. To check for stationarity the fund distribution is plotted against time. From Figure 3 we see that both the median and average inflation-adjusted fund size have remained roughly constant over the sample period. Hence, the growth in the Nordic hedge fund industry is mainly caused by growth in the number of hedge funds, as we see from the light blue line, rather than fund size. Therefore, we consider the estimates of the average value added per fund is to be stationary.

Fund Size Distribution

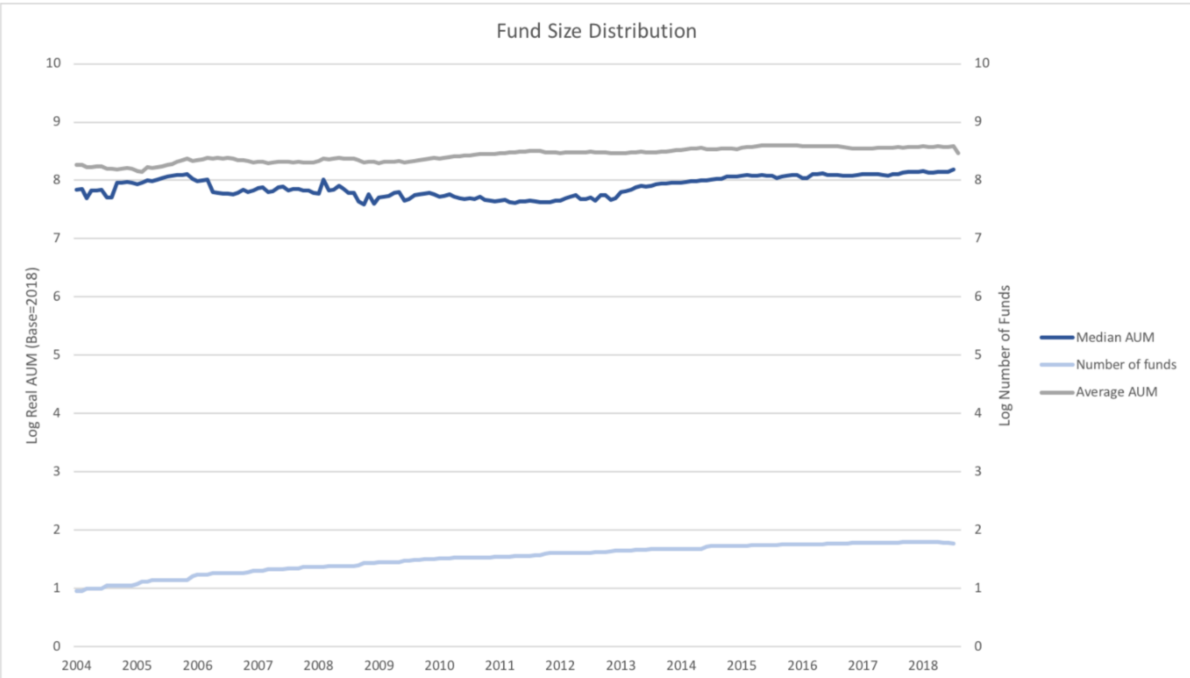

***Figure 3**: The graph displays the logarithmic growth in number of funds and real assets under management in $ (base year 2018) for Jan 04-Aug 18. The grey line represents the average real AUM of all funds, the dark blue line shows the median of real AUM of all funds and the light blue line represents the total number of funds.*

Factor Models

Table 11 reports the results from regressions of CAPM, Fama-French 3-factor model, Carhart 4-factor model, and Fung-Hsieh 7-factor and 9-factor model. The unsmoothed returns of the value weighted Nordic hedge fund market are regressed on the risk factors in each model. The CAPM contains no significant risk factors, and the R^2 is 0.6%. Further, both the Fama-French 3-factor model (FF3F) and the Carhart 4-factor model (C4F) only have one significant risk factor each, and their R^2 are 4.2% and 4.7% respectively. These results suggest that CAPM, Fama-French 3-factor model and Carhart 4-factor model explain little of the variation in the Nordic hedge fund performance. Further, both the Fung-Hsieh 7-factor (FH7F) and 9-factor (FH9F) model contain two significant risk factors each, and their explanatory powers are relatively similar (22.3% vs. 22.9%). However, as none of the two factors added in the Fung-Hsieh 9-factor model are significant, we rather choose the 7-factor model for further analyses as we would lose two degrees of freedom in the 9-factor model.

The Akaike information criterion (AIC) measures how much information we lose from the regression model, and the Bayesian information criterion (BIC) measures exactly the same as the AIC, but it penalizes the use of degrees of freedom even harder than the AIC. Both criterions are considered as alternatives to the traditional R^2 criterion, and the lower the value of AIC and BIC, the better is the model (Gregoriou & Pascalau, 2011). From Table 11 we see that both the AIC and BIC criterion indicate that the Fung-Hsieh 7-factor model is the best model in explaining Nordic hedge fund performance. Hence, the AIC and BIC criterion support our choice of model in the paragraph above. Nevertheless, it is worth noting that the AIC and BIC values are marginally different between the five models.

Comparison of Factor Models

	(1) Market	(2) Market	(3) Market	(4) Market	(5) Market
MKT-RF	0.0249	0.0486	0.0551*		
	(0.0239)	(0.0259)	(0.0266)		
SMB		-0.0483	-0.0512		
		(0.0434)	(0.0435)		
HML		-0.0856*	-0.0712		
		(0.0385)	(0.0411)		
Mom			0.0238		
			(0.0238)		
SPCOMP				0.0325	0.0315
				(0.0227)	(0.0228)
SCMLC				0.0196	0.0199
				(0.0351)	(0.0352)
BD10RET				-1.282**	-1.330**
				(0.431)	(0.446)
BAAMTSY				-0.366	-0.394
				(0.460)	(0.514)
PTFSBD				0.00136	0.000849
				(0.00737)	(0.00745)
PTFSFX				0.0253***	0.0251***
				(0.00541)	(0.00543)
PTFSCOM				0.00352	0.00352
				(0.00611)	(0.00621)
PTFSIR					-0.00259
					(0.00351)
PTFSSTK					0.00703
					(0.00686)
Constant	0.00420***	0.00406***	0.00399***	0.00538***	0.00562***
	(0.000954)	(0.000944)	(0.000947)	(0.000895)	(0.000941)
Observations	176	176	176	176	176
R^2	0.006	0.042	0.047	0.223	0.229
AIC	-1042.7	-1045.2	-1044.2	-1074.4	-1071.8
BIC	-1036.4	-1032.5	-1028.3	-1049.0	-1040.1

Table 11*: The table presents the results from the regressions of the five linear factor models. In each regression the unsmoothed returns of the value weighted Nordic hedge fund market are regressed on the risk factors in the respective model. The R^2, AIC and BIC are statistical properties of the distribution. Standard errors are presented in parentheses, where *p<0.05, **p<0.01 and ***p <0.001.*

Stepwise Regression

We conduct a stepwise regression analysis to test if we can improve the Fung-Hsieh 7-factor model by adding additional risk factors to the model. The process of selecting which additional risk factors to include in our model is based on the presented risk factors in Section 2.1. Additional risk factors are added to our 7-factor model as long as they are significantly related to hedge fund returns. The results of the analyses are presented in Table 12 and 13.

Stepwise Regression: Fung-Hsieh 7-factor Model (FH7F)

	(1) FH7F	(2) FH7F	(3) FH7F	(4) FH7F	(5) FH7F	(6) FH7F
SPCOMP	0.0325	0.0311	0.0336	0.0329	0.0392	0.0650**
	(0.0227)	(0.0335)	(0.0227)	(0.0228)	(0.0233)	(0.0220)
SCMLC	0.0196	0.0197	0.0161	0.0197	0.0166	0.0280
	(0.0351)	(0.0353)	(0.0351)	(0.0352)	(0.0351)	(0.0327)
BD10RET	-1.282**	-1.280**	-1.215**	-1.291**	-1.343**	-1.159**
	(0.431)	(0.434)	(0.432)	(0.431)	(0.433)	(0.401)
BAAMTSY	-0.366	-0.361	-0.401	-0.457	-0.545	0.642
	(0.460)	(0.470)	(0.460)	(0.478)	(0.481)	(0.469)
PTFSBD	0.00136	0.00142	0.00101	0.00132	0.000963	0.00717
	(0.00737)	(0.00745)	(0.00736)	(0.00739)	(0.00737)	(0.00694)
PTFSFX	0.0253***	0.0252***	0.0254***	0.0253***	0.0249***	0.0248***
	(0.00541)	(0.00551)	(0.00540)	(0.00542)	(0.00541)	(0.00503)
PTFSCOM	0.00352	0.00358	0.00338	0.00314	0.00293	0.00758
	(0.00611)	(0.00624)	(0.00610)	(0.00614)	(0.00612)	(0.00573)
MSCI EM		0.00127				
		(0.0223)				
HML			-0.0465			
			(0.0345)			
MOM				0.0149		
				(0.0206)		
TED					0.280	
					(0.224)	
VIX						-0.0218***
						(0.00416)
Constant	0.00538***	0.00538***	0.00536***	0.00535***	0.00404**	0.00582***
	(0.000895)	(0.000898)	(0.000893)	(0.000897)	(0.00140)	(0.000836)
Observations	176	176	176	176	176	176
R^2	0.223	0.223	0.231	0.225	0.230	0.332
AIC	-1074.4	-1072.4	-1074.3	-1072.9	-1074.0	-1099.1
BIC	-1049.0	-1043.9	-1045.8	-1044.4	-1045.5	-1070.6

Table 12*: The table provides the results from five stepwise regressions of the Fung-Hsieh 7-factor model. In each regression the unsmoothed returns of the value*

*weighted Nordic hedge fund market are regressed on the Fung-Hsieh risk factors and an additional risk factor. The R^2, AIC and BIC are statistical properties of the distribution. Standard errors are presented in parentheses, where *p<0.05, **p<0.01 and ***p <0.001.*

Stepwise Regression: Extended Fung-Hsieh 7-factor Model (EFH7F)

	(1) EFH7F	(2) EFH7F	(3) EFH7F	(4) EFH7F	(5) EFH7F
SPCOMP	0.0650**	0.0663*	0.0651**	0.0651**	0.0704**
	(0.0220)	(0.0319)	(0.0220)	(0.0221)	(0.0225)
SCMLC	0.0280	0.0280	0.0256	0.0281	0.0254
	(0.0327)	(0.0328)	(0.0328)	(0.0328)	(0.0327)
BD10RET	-1.159**	-1.161**	-1.119**	-1.166**	-1.212**
	(0.401)	(0.404)	(0.403)	(0.402)	(0.403)
BAAMTSY	0.642	0.637	0.601	0.572	0.481
	(0.469)	(0.477)	(0.472)	(0.486)	(0.489)
PTFSBD	0.00717	0.00712	0.00684	0.00711	0.00678
	(0.00694)	(0.00702)	(0.00696)	(0.00696)	(0.00695)
PTFSFX	0.0248***	0.0249***	0.0249***	0.0248***	0.0244***
	(0.00503)	(0.00512)	(0.00503)	(0.00504)	(0.00503)
PTFSCOM	0.00758	0.00752	0.00742	0.00729	0.00705
	(0.00573)	(0.00585)	(0.00574)	(0.00577)	(0.00575)
VIX	-0.0218***	-0.0218***	-0.0214***	-0.0217***	-0.0216***
	(0.00416)	(0.00417)	(0.00418)	(0.00417)	(0.00416)
MSCI EM		-0.00119			
		(0.0207)			
HML			-0.0296		
			(0.0324)		
MOM				0.0107	
				(0.0192)	
TED					0.238
					(0.209)
Constant	0.00582***	0.00582***	0.00580***	0.00580***	0.00467***
	(0.000836)	(0.000839)	(0.000837)	(0.000839)	(0.00131)
Observations	176	176	176	176	176
R^2	0.332	0.332	0.336	0.334	0.337
AIC	-1099.1	-1097.1	-1098.0	-1097.5	-1098.5
BIC	-1070.6	-1065.4	-1066.3	-1065.8	-1066.8

***Table 13**: The table presents the results from five stepwise regressions of the extended Fung-Hsieh 7-factor model. In each regression the unsmoothed returns of the value weighted Nordic hedge fund market are regressed on the extended Fung-Hsieh risk factors and an additional risk factor. The R^2, AIC and BIC are statistical properties of the distribution. Standard errors are presented in parentheses, where *p<0.05, **p<0.01 and ***p <0.001.*

From the results presented in table 12 and 13, we only find the aggregate volatility factor (VIX factor) to be significantly related to Nordic hedge fund returns. Since the VIX index increases as market uncertainty increases and investors are turning pessimistic, the VIX factor is inversely related to hedge fund performance. So, by trading options on the VIX Index, Nordic hedge fund managers can potentially achieve diversification benefits and/or eliminate the skew and excess kurtosis that many hedge fund strategies exhibit (Black, 2006; Daigler & Rossi, 2006). By adding the VIX factor to the Fung-Hsieh 7-factor model, the explanatory power of the model increase from 22.3% to 33.2%. The increase in the explanatory power indicates that either the VIX factor is able to explain much of the variation in Nordic hedge fund returns, or that some of the Fung-Hsieh factors are strongly correlated to the VIX factor. In addition, both the AIC and BIC improve when adding the VIX factor to the model. Hence, we add the VIX factor to the Fung-Hsieh 7-factor model. Further analyses on value added are based on this 8-factor model.

Risk Factors

Based on the results from the model comparison and stepwise regression, we decide to use the Fung-Hsieh 7-factor model and the VIX factor to estimate value added for the hedge funds in our database. A description of each risk factor and how it is collected or constructed is presented in Section 6. Table 14 presents descriptive statistics of the eight risk factors and Table 15 presents the correlation matrix for all the risk factors.

Descriptive Statistics of Risk Factors

Factor	Mean	P_{25}	Median	P_{75}	St.Dev	n
SPCOMP	0.0065	-0.0139	0.0119	0.0291	0.0445	176
SCMLC	0.0016	-0.0156	0.0028	0.0159	0.0269	176
BD10RET	-0.0001	-0.0015	0.0010	0.0013	0.0024	176
BAAMTSY	0.0000	-0.0010	-0.0001	0.0008	0.0023	176
PTFSBD	-0.0371	-0.1366	-0.0658	0.0202	0.1422	176
PTFSFX	-0.0123	-0.1565	-0.0603	0.0819	0.1950	176
PTFSCOM	-0.0030	-0.1049	-0.0336	0.0703	0.1479	176
VIX	0.0189	-0.1105	-0.0167	0.1082	0.2230	176

***Table 14**: The table presents descriptive statistics of the risk factors used in our final model. The table is calculated from monthly observations from January 2004 to August 2018.*

Correlation Matrix of Risk Factors

	SPCOMP	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	VIX
SPCOMP	1.0000							
SCMLC	0.3926	1.0000						
BD10RET	0.3208	0.2001	1.0000					
BAAMTSY	0.4011	0.1288	0.4719	1.0000				
PTFSBD	0.1438	0.1652	0.3749	0.3097	1.0000			
PTFSFX	0.1412	0.0577	0.0933	0.3229	0.4647	1.0000		
PTFSCOM	0.0352	0.0129	0.0685	0.1604	0.2041	0.3461	1.0000	
VIX	0.1186	0.0867	0.1292	0.3877	0.2590	0.2105	0.2137	1.0000

***Table 15**: The table provides the correlation between the risk factors used in our final model from January 2004 to August 2018.*