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Master Thesis

An Examination of the Risk-Return Profile of Nordic Hedge Funds

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Abstract

The Nordic hedge fund industry has experienced a massive growth in assets under management of approximately 370% between 2005 and 2016. The increased interest for hedge funds as an investment vehicle may suggest that investors believe that Nordic hedge fund managers are able to deliver risk-adjusted excess returns. In this paper, we aim to provide a better understanding of the risk-return profile of Nordic hedge funds. Using traditional linear risk factor models, we find that Nordic hedge funds apparently creates statistical significant pre-fee alphas between 6% and 8% during the period between January 2005 and December 2016. However, empirical studies suggest that hedge fund returns exhibit significant left-tail risk and that the traditional mean-variance framework fails to capture the true risk profile of hedge funds. Furthermore, studies show that hedge fund returns resembles the returns of an uncovered index put option. This further support our belief that traditional linear risk factor models are inappropriate in order to account for the performance of hedge funds and gives motivation to apply alternative methods when studying the risk and return for Nordic hedge funds. We show that a mechanic put-writing strategy largely accounts for the net-of-fee alphas of Nordic hedge funds, but not the pre-fee alphas. However, this result hinges critically on the accuracy of the NHX reporting process. A small degree of return smoothing or presence of backfill bias or survivorship bias could potentially leave the pre-fee alphas insignificant or even negative. These findings enhances our understanding of hedge funds in aggregate, and they may provide the basis for a more sober evaluation of Nordic hedge funds as investment vehicles.

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1.0 Introduction

During the last three decades, the total amount of global hedge fund assets under management (AuM) grew from USD 50 billion to reach USD 3.02 trillion in 2016.[1] The Nordic hedge fund industry has followed a similar trend. In 2016, the total assets under management of Nordic hedge funds amounted to about USD 48 billion[2], making the Nordic hedge funds interesting from a growth and size point of view. Given the lack of transparency in hedge fund reporting standards and high hedge fund fees, it is not unreasonable to assume investors believe that Nordic hedge fund managers are able to deliver risk-adjusted excess returns over time. This provides motivation to seek a better understanding of the risk-return profile of these funds. In this thesis, we ask the question: How can the risk-return profile of Nordic hedge funds be accounted for?

We use the Nordic hedge fund composite index (NHX) as a proxy for the Nordic hedge fund universe, and the S&P 500 index as the benchmark to compare the performance of this proxy. Further, we review the flaws of existing hedge fund indices, and start our examination of Nordic Hedge funds by comparing the descriptive statistics of the NHX to those of the market benchmark.

The empirical literature on hedge fund returns have mainly emphasized regressions on index returns onto various factors. In order to examine the Nordic hedge funds performance, we find it natural to start with traditional linear risk factor models such as the CAPM, Fama-French/Carhart factor models and the Fung-Hsieh nine-factor model. The single factor model CAPM alongside with the multifactor models Fama-French/Carhart are commonly used in assessing the performance of traditional fund managers. The Fung-Hsieh nine-factor model was especially developed to explain the performance of well-diversified hedge fund portfolios.

We find that these traditional linear risk factor models are not able to explain the risk-return profile of the Nordic hedge funds. Consequently, we further review the

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[1] Source: Hedge Fund Research
https://www.hedgefundresearch.com/family-indices/hfri
[2] Source: Preqin Alternative Assets Data and Intelligence
https://www.preqin.com/format/hedge-funds-publications/2/1

literature on empirical hedge fund risk-return characteristics, which e.g. argues that traditional mean-variance frameworks are inappropriate in order to explain the performance of hedge funds (Goetzmann et. al., 2004). Empirical research suggests that typically, hedge fund returns exhibit significant left-tail risk, leading linear risk factor models to underestimate the true risk of hedge funds (Fung & Hsieh, 1997). Furthermore, hedge fund research argues that hedge fund managers employ strategies with almost zero correlation with the market when the market experience growth, but large positive correlation with the market during market declines (Mitchell & Pulvino, 2001). Such strategies exhibit returns that are reminiscent to the returns of uncovered index call and put option strategies (Agarwal & Naik, 2004). Finally, Jurek & Stafford (2015) find that the HFRI Fund Weighted Composite index[3] risk-return profile can be replicated with an alternative nonlinear model. They argue that hedge fund managers specialize in bearing downside market risk and suggest a mechanic put-writing strategy in order to describe the risk-return profile of hedge funds with a more accurate, alternative method to traditional risk-factor models.

In this paper, we use this strategy to test the performance of Nordic hedge funds. The model aims to replicate the risk-return profile of Nordic hedge funds based on a strategy to write short-dated put options on the S&P 500 index, with different levels of leverage and option strike prices. This strategy collects the short option premium as long as the market, represented by the S&P 500 performs well, neutral or even poor. However, if the stock market is exposed to extreme declines, this strategy will experience huge losses.

In the remainder of this paper, we present the results of the various put-writing strategies. Further, in our analysis, we discuss the usefulness of traditional linear risk factor models and the alternative put-writing strategy when assessing the risk-return profile of Nordic hedge funds. The flaws of hedge fund indices are further revisited and discussed in conjunction with the results of the put-writing strategies. Finally, a conclusion is presented, summing up our findings.

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[3] The HRFI Fund Weighted Composite Index is a broad hedge fund index constructed to capture hedge fund performance across all strategies and regions. The index includes over 2000 hedge funds and are equally weighted.
https://www.hedgefundresearch.com/hfri-indices-index-descriptions

2.0 Data Description

We start our research of hedge funds returns by assessing the Nordic Hedge Fund Composite Index (NHX) as a proxy for the Nordic hedge fund universe (HedgeNordic). The NHX is a broad Nordic hedge fund index, designed to capture the breadth of the Nordic hedge fund industry performance across all strategies and asset classes. The index is net-of-fees, non-investible and consists of 157 active and reporting hedge funds from five Nordic countries: Norway, Sweden, Denmark, Finland and Iceland, with monthly observations in the period between January 2005 and January 2017 (144 observations). Because the NHX is based on a database where hedge funds reports to, it is especially prone to biases. Furthermore, hedge funds often hold illiquid assets whose true value is slowly reflected in reported returns (Huang, Liechty & Rossi, 2012). This could result in a wrongful interpretation of hedge fund returns because the reported returns can end up as a smoothed version of its true realized returns when reported. Finally, the NHX is reported net-of-fees, which complicates the evaluation of the NHX performance. We will discuss these hedge fund index characteristics further in the section below.

2.1 Hedge Fund Biases

Hedge funds are not subject to any reporting standards regarding their returns, investment strategies or holdings. This leads to three distinctive hedge fund biases (Malkiel & Saha, 2005):

1. Survivorship bias.
2. Backfill bias.

Firstly, hedge fund indices only provide information regarding operating funds, which creates a survivorship bias because the not operating funds, which have underperformed, are removed from the index. Survivorship bias estimates range between 0.16% (Ackermann, McEnally & Ravenscraft, 1999) and 4.5% (Malkiel & Saha, 2005) per year.

Secondly, hedge funds are not required to make public disclosure and are not automatically incorporated in a database when they are incepted; but if their performance proves to be good, they may be entered in a database in order to

attract new investors. They hence creates a backfill bias when the fund with positive past performance is incorporated in the database. Previous studies have found backfill bias estimates of 3.6% per year (Fung & Hsieh, 2000).

These biases could be inherent from the Hedge Nordic database to the NHX, and we will have to consider this when evaluating the performance of the NHX.

2.2 Return Smoothing

Empirical studies on downside risk exposure in hedge funds show that analyzing the reported returns is complicated by the presence of return smoothing during lock-up periods, when investors are not allowed to sell shares ((Bollen & Pool, 2009), (Getmansky, Lo & Marakov, 2004)). Hedge funds often involve in illiquid assets whose true value are difficult to price. This enables the hedge fund managers to smoothen the returns by picking low estimations of the asset when the price are high, and high estimates of the asset when the price are low. This is done so that the hedge fund managers are able to distribute great losses over a longer time period in order to make the fund appear less volatile. Huang, Liechty & Rossi (2012) argues that even a moderate level of return smoothing can cause to over-estimate hedge funds abnormal excess returns, alpha, by more than 2% annually. This may result in a wrongful interpretation when evaluating the true risk profile of the NHX.

2.3 Fee Structure of Hedge Funds

The NHX is reported net-of-fees. In order to quantify the hedge fund fees, we apply the high watermark standard, i.e. charging a flat fee of 2% and a 10% incentive fee, both payable monthly. The high watermark standard is constructed such that whenever the hedge fund delivers a positive return, the level on which the hedge fund manager receives the incentive fee moves upwards. This is done to ensure that the investor does not pay a double incentive fee for a single period of return. We define the difference between the pre-fee return and net-of-fee return as all-in investor fee. Studies done on all-in fees suggest that the historical all-in fees amount to approximately 3% to 4%. Ibbotson, Chen & Zhu (2010) find that the average fund earned an all-in fee of 3.43% in the period between 1995 and 2009 using cross-sectional data from the TASS database. French (2008) finds a total all-in fee of 4.26% for equity-related U.S. hedge funds based on data from the HFRI database in the sample period between 1996 and 2007.

Jurek & Stafford estimates an all-in-fee of 3.8% for the Dow Jones/Credit Suisse (DJSC) Broad Hedge Fund Index and the equal-weighted HFRI Fund Weighted Composite Index during the period January 1996 to June 2012. When we estimate the NHX pre-fee returns, we add the above mentioned empirical all-in fee to the NHX net-of-fee returns.

2.3 Descriptive Statistics

The next step in our study of the NHX is a simple comparison between the historical NHX performance with the historical performance of the U.S. stock market and the Nordic stock market represented by Standard & Poor's 500 Composite Index (S&P 500) and the OMX Nordic 40 Index (OMXN 40) respectively. Figure 1 reports the cumulative monthly returns of the S&P 500 index, the OMXN 40 index and the pre-fee NHX, over the same period from January 2005 to January 2017. The pre-fee NHX apparently delivers higher cumulative returns than the S&P 500 and the OMXN 40. In order to conduct a more comprehensive descriptive analysis, we summarize the mean return, the volatility, measured by the standard deviation, the Sharpe Ratios (Sharpe, 1966), the CAPM betas[4] and the drawdowns of the NHX, the OMXN 40 and the S&P 500 index in table 1. The Sharpe Ratio is given by the formula:

$$SR_i = \frac{E[R_i] - r_f}{\sigma_i} \tag{1}$$

Where SR_i is the Sharpe Ratio of asset i, $E[R_i]$ is the expected return of asset i, r is the risk-free rate, represented by the 10-years U.S. Treasury bond, and σ_i is the volatility of asset i. We find that the Sharpe Ratio (SR) of the NHX is 1.53, the SR of OMNX 40 is 0.26 and the SR of the S&P 500 index is 0.36. The linear systematic risk exposure (CAPM β) indicates that the NHX is largely uncorrelated to the return of the stock market indices. Studying the drawdowns, the NHX also performs well. The reported drawdown is the maximum drawdown (MDD) over the sample period, given by the formula:

$$MDD = \frac{(P - L)}{P} \tag{2}$$

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[4]The CAPM betas are extracted from the CAPM regression, $\bar{r}_i = r_f + \beta_i(\bar{r}_m - r_f) + \varepsilon_{i,t}$ (Sharpe, 1964), (Lintner, 1965), (Mossin, 1966) where the beta represents the volatility of a portfolio in comparison to the market.

Where P is the peak value before the largest drop, and L is the lowest value before new growth period starts. The maximum drawdown is an indicator of the downside risk, experienced over the entire sample period, measuring the magnitude of the decrease in the value of the investment relative to its highest historical value. With a drawdown of -11.23%, the NHX has a substantially lower drawdown compared to the S&P 500 index and the OMXN 40 with -52.56% and -61.06% respectively.

Our descriptive analysis implies that the NHX performs significantly better than a buy and hold strategy on the S&P 500 or the OMXN 40. With a drawdown that is almost one fifth of the drawdowns of the S&P 500 index and a CAPM beta of only 0.25, the NHX appears almost as market neutral. In order to study the performance of the NHX in more detail, we examine whether traditional linear risk-factor models such as the CAPM, Fama-French three-factor model, Carhart four-factor model and the Fung-Hsieh nine-factor model can explain the performance of the NHX.

Figure 1.
Cumulative Return for S&P 500, OMXN 40 and NHX pre-fee
The figure shows the cumulative value of investing 100 NOK in S&P 500, OMXN 40 and Nordic hedge index pre-fee from 1. January 2005 to 1. January 2017 (144 months). OMXN 40 represents the 40 most-traded stock classes of shares from the Nordic stock market.
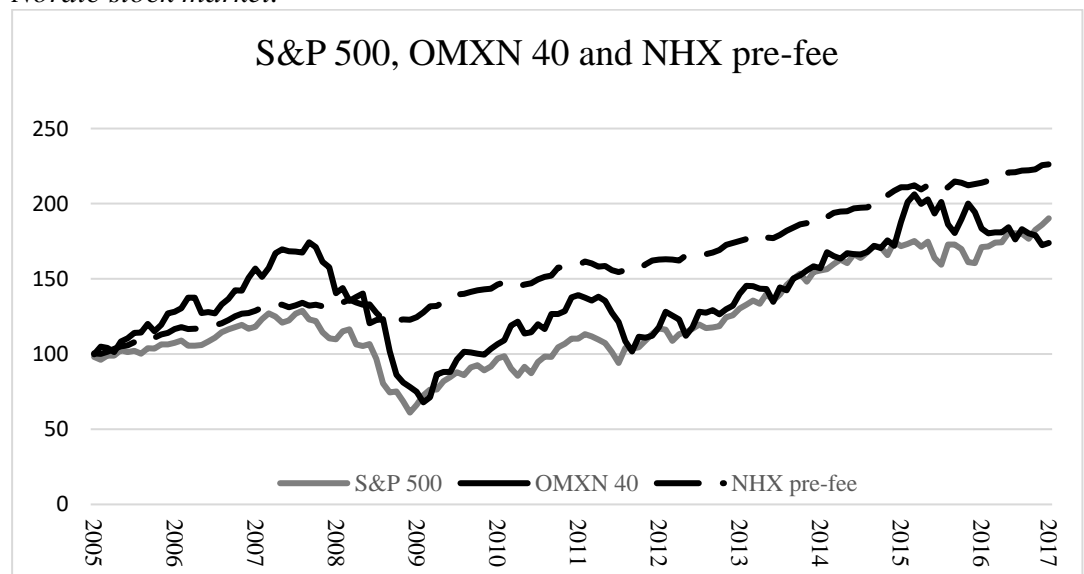
Table 1.
Historical Performance of the NHX *pre-fee*, OMXN 40 and S&P 500
The table shows descriptive statistics for the NHX pre-fee, OMXN 40 and S&P 500 over the sample period (1. January 2005 to 1. January 2017, 144 monthly observations). The volatility is measured by the standard deviation, and the risk-free rate in the Sharpe Ratio (1) is the average risk-free rate from a 10-year US treasury bond. The CAPM β are the average beta during the sample period extracted from equation 3. The drawdown are maximum drawdown experienced in the period, calculated using equation 2.

Asset	Mean	Volatility	SR	CAPM β	Drawdown
S&P 500	6.63%	15.16%	0.36	1	-52.56%
NHX	7.17%	4.96%	1.53	0.25	-11.28%
OMXN 40	6.40%	17.64%	0.26	0.91	-61.06%

3.0 Factor Models

Risk factor models are commonly used to identify the main characteristics and the risk exposure of portfolios. In this section, we investigate whether the traditional linear risk factor models[5] are able to explain the risk-return profile of the NHX. For each risk factor model, we define the regressions and report the results. In the last part of this section we summarize our findings, and our estimates are provided in table 2 and figure 2 (see appendix 10.2-10.3 for distortion analysis and full descriptive statistics for the factor models).

3.1 Capital Asset Pricing Model (CAPM)

We start with the Capital Asset Pricing Model (CAPM) ((Sharpe, 1964), (Lintner, 1965), (Mossin, 1966)) where we describe the relationship between the systematic risk and expected return for the NHX. The CAPM is given by the formula:

$$\text{CAPM:} \quad \bar{r}_i = r_f + \beta_i(\bar{r}_m - r_f) + \varepsilon_{i,t} \tag{3}$$

Where $\bar{r}_i$ is the expected return of security i, r_f is the risk free rate, β_i is the beta of security i and reflects the portfolios sensitivity against the stock market and $\bar{r}_m$ is the expected market return.

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[5] For each factor model we apply the S&P 500 to represent the market and the risk-free rate is the 10- year U.S Treasury bond yield. The respective risk factors are extracted from the database of Kenneth R. French: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html and David A. Hsieh: https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm

Our estimates suggest that the CAPM is unable to explain the performance of the NHX, as the NHX performs a positive statistical significant net-of-fees annualized alpha of 3% throughout the sample period with an adjusted R^2 of 46.67% relative to the CAPM. This is an interesting result, if we add the all-in-fee, the NHX delivers a positive significant alpha of approximately 6%.

3.2 Fama-French Three-Factor Model

As an extension to the CAPM we employ the Fama-French three-factor model (Fama & French, 1993), we want to investigate whether the Fama-French factors can explain the risk and returns in a better way than the CAPM. The Fama-French three-factor model is given by:

$$R_{it} - R_{ft} = \alpha_i + \beta_{im}(R_{mt} - R_{rf}) + \beta_{iSMB}SMB_t + \beta_{iHML}HML_t + \varepsilon_{i,t} \quad (4)$$

Where SMB (Small minus big), represents the return of a portfolio consisting of small cap stocks in excess of return on a portfolio consisting of large cap stocks. High minus low (HML) represents the return of a portfolio of stocks with a high book-to-market ratio in excess of the return on a portfolio consisting of stocks with a low book-to-market ratio. The β's represent the portfolios sensitivity to their respective risk factors.

The Fama-French three-factor model indicates that the NHX performs a positive significant net-of-fees alpha of 3.7445% with an adjusted R^2 of 47.45%.

3.3 Carhart Four-Factor Model

We further apply the Carhart's four-factor model (Carhart, 1997) which is an extension to the Fama-French three-factor model where the momentum factor (MOM) is added. The Carhart four-factor model is given by the formula:

$$R_{it} - R_{ft} = \alpha_i + \beta_{im}(R_{mt} - R_{rf}) + \beta_{iSMB}SMB_t + \beta_{iHML}HML_t +$$
$$\beta_{iMOM}MOM_t + \varepsilon_{it} \quad (5)$$

Momentum (MOM) represents the return of a portfolio consisting of positive momentum stocks in excess of return on a portfolio consisting of stocks with negative momentum.

The Carhart four-factor model is also unable to explain the cross-sectional return and suggests that the NHX delivers a positive significant net-of-fees alpha of 3.738% with an adjusted R^2 of 49.48%.

3.4 Fung-Hsieh Nine-Factor Model

The CAPM, Fama-French/Carhart models fail to explain the performance of the NHX. Fung & Hsieh (1997, 2001, 2004) argue that hedge fund returns can be explained with "asset-based" hedge-fund style factors. They extract common components using observable market risk factors from hedge fund strategies such as merger arbitrage, fixed-income, equity long/short and trend following strategies in order to explain hedge funds returns. The Fung & Hsieh trend following factor extends the work of Merton (1981) that trend followers make money when the markets are volatile, similar to option strategies and suggest that hedge fund trading strategies have option-like returns. They suggest a "Primitive Trend-following Strategy"[6] (PTFS), which have similar payouts as a "lookback option straddle". The PTFS aims to capture largest price movements achieved over a time interval. Based on the research of Fung-Hsieh we construct the Fung-Hsieh nine-factor model:

$$R_{i,t} = \alpha_i + \beta_{i,MKT}SP500_t + \beta_{i,SIZE}SIZE_t + \beta_{i,TSY}TSY_t + \beta_{i,CREDIT}CREDIT_t + \beta_{i,PTFSBD}PTFSBD_t + \beta_{i,PTFSFX}PTFSFX_t + \beta_{i,PTFSCOM}PTFSCOM_t + \beta_{i,PTFSIR}PTFSIR_t + \beta_{i,PTFSSTK}PTFSSTK_t + \varepsilon_{i,t}$$

$$(6)$$

The two first risk factors are equity orientated factors, SP500 represents the market factor and the SIZE factor are extracted from equity long/short hedge funds strategies, and represents the Russell 2000 less the S&P 500 index. The two next factors are bond orientated risk factors, the TSY represents the monthly change in the 10-year treasury yield and the CREDIT factor represents Moody's Baa yield less the 10-year treasury yield which are extracted from fixed-income hedge fund strategies. The last five factors represents the trend following hedge fund strategies, the PTFSBD, PTFSFX, PTFSCOM, PTFSIR and the PTFSSTK

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[6] The Primitive Trend-Following Strategy represents a single trade over a given time interval with a buy-and-hold strategy, where the investor buys at the beginning and sells at the end of the period. Let S, S', S_{max} and S_{min} represent the initial asset price, ending price, maximum price and minimum price over a given time interval. The PTFS aims to capture the largest price movement during the time interval which yields the optimal payoff $S_{max} - S_{min}$ (Fung-Hsieh, 2001).

factors represents the Fung-Hsieh primitive trend-following strategy measured as the return of lookback options on bonds, currency, commodities, interest rates and stocks respectively.

The Fung-Hsieh nine-factor model are also unable to explain the performance of the NHX. Even with the hedge fund specialized asset based risk factors the nine-factor model yields a positive significant net-of-fees alpha of 3.14% with an adjusted R^2 of 49.49%.

3.5 Factor Model Summary

We find that Nordic hedge fund manager's apparently delivers statistical significant *pre-fee* alphas between 6% and 8% yearly relative to traditional risk factor models such as the CAPM, Fama-French three factor model, Carhart four-factor model and Fung-Hsieh nine factor model. Even after deducting hedge fund fees, these results makes hedge funds appear as attractive investment vehicles and implies a significant market inefficiency relative to other areas of active investment management (Fama & French, 2010). In contrast, empirical studies documents that mutual funds creates pre-fee alphas that are indistinguishable from zero.

Table 2 reports the results from the regressions of Nordic hedge funds on the traditional risk-factor model. The adjusted R^2s ranging between 46.67% (CAPM) and 49.48% (Fung-Hsieh) implying a good overall fit. The market factor (MKT) is the only factor that is statistically significant for all models, while the high-minus-low (HML) factor is statistically significant for all the multifactor models. For the Fung-Hsieh nine-factor model, only three of the additional factors, CREDIT, PTFSFX and PTFSIR are statistically different from zero, and their net contribution to the model is negative, which implies that the factors should be excluded from the model in order to explain the returns of the NHX. These results indicates two possible explanations:

- Firstly, there is a degree of market inefficiency (Fama & French, 2010) and the possibility that Nordic hedge fund managers simply outperform the market and creates true alphas.

- Secondly, the proposed traditional risk-factor models fail to explain the true risk-return profile of Nordic hedge funds.

These results rests on the assumption that there are no significant presence of return smoothing or hedge fund biases in the NHX. We can assume that it is unlikely that the true risks are lower than those estimated. To understand why the traditional risk-factor models have trouble explaining the performance of the NHX, we examine the risk properties of alternative investments. If the risk characteristics of the NHX are different from the risk characteristics of traditional asset classes, we have to consider alternative models when evaluating the performance of the NHX.

We summarize the regressions in table 2 and figure 2 below. All reported alphas are statistically significant on a 1% level.

Table 2: Summary statistics, linear factor models

This table report the regression alpha along with the adjusted R-squared and the beta for each factor in the respective models. The set of common risk factors includes the Fama-French (1993) factors, the momentum factors of Carhart (1997) and the factors of Fung-Hsieh (2004). *, **, and *** represents the significant level on respectively 10%, 5% and 1%. The data sample consists of 144 monthly observations from 1.January 2005 to 1. January 2017. The equation for each factor model are found in section 2.

	Alpha	Adj. R-squared	MKT-RF	SMB	HML	MOM
CAPM	2.95% ***	46.67%	0.25***			
Fama-French	3.75% ***	47.45%	0.19***	-0.07	-0.06**	
Carhart	3.78% ***	49.478%	0.2***	-0.007	-0.063**	0.019

	Alpha	Adj. R-Squared	SP500	SIZE	TSY	CRED	TFBD	TFFX	TFCOM	TFIR	TFSTK
Fung-Hsieh	3.84% ***	49.49%	0.171***	-0.005	-0.029	-0.043**	-0.002	0.009**	-0.001	-0.007***	0.0005

Figure 2.
Cumulative return for each factor model
This table plots the cumulative return for 100 NOK invested in each of the factor models from first of January 2005 to first of January 2017, exclusive the estimated intercept. In comparison, we show the plotted risk-free rate which is the 10-year US Treasury bond, and NHX is the Nordic hedge index *Net-of-fees*.
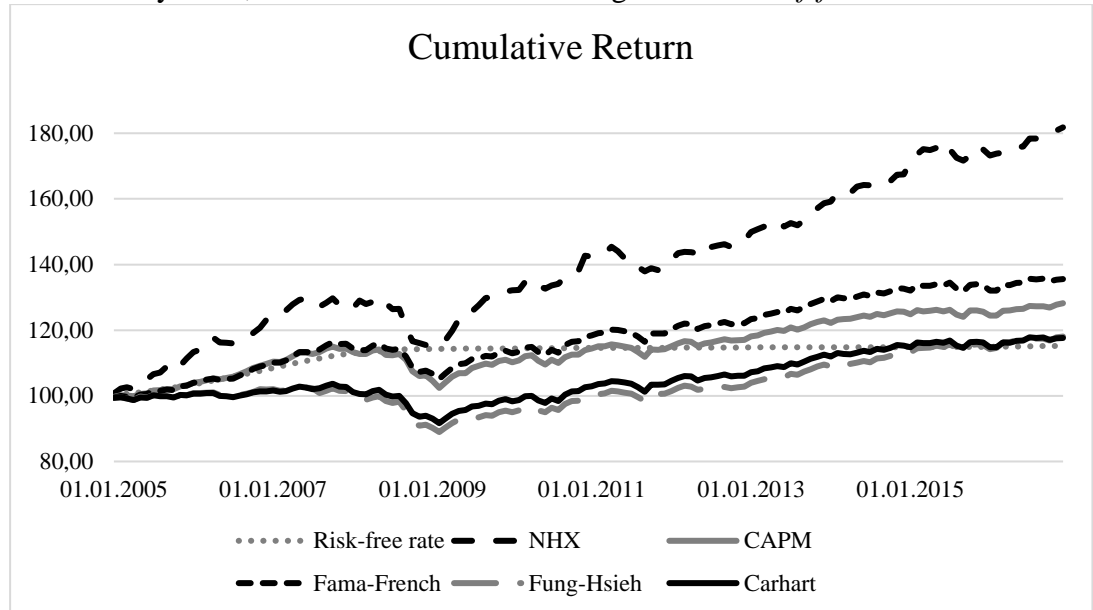
4.0 Risk Properties of Nordic Hedge Funds

Mitchell & Pulvino (2009) documents that hedge funds bears nonlinear risks that tend to yield returns during poor economic conditions and when the stock market performs poorly. This could explain why the traditional linear risk factor models are unable to explain the compounded performance of the NHX. In order to evaluate the NHX performance further, we need to explore the risk-properties of Nordic hedge funds. This could give us valuable insight on why the proposed traditional risk factor models fails to explain the NHX returns.

4.1 Hedge Funds Risk Exposure

In the paper "Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds (1997)", William Fung & David A. Hsieh suggest that hedge fund managers typically take a lower exposure to traditional market factors, such as the global bond market, stock indices and the slope of the treasury yield curve and the change in investment grade credit spreads. They claim that this leads to significant left-tail risk. In a mean-variance framework, one of the assumptions behind this framework is that the investment returns are normally distributed.

Consequently, if the hedge fund returns were prone to a significant left-tail risk, the traditional mean-variance based risk-factor models would underestimate the riskiness of hedge fund returns.

In an extension on the work of Fung & Hsieh (1997), Agarwal & Naik (2004) argue that hedge fund managers typically employ dynamic trading strategies that seek to realize when the rest of the stock market performs poorly. These strategies can often be replicated with put and call options, such as a merger arbitrage strategy, or leverage buyout strategies. Common for these strategies is that they tend to realize, as long the market does not experience extreme negative declines. In the paper "Characteristics of Risk and Return in Risk Arbitrage (2001)", Mitchell & Pulvino find that the risk characteristics of these strategies have similarities to the risk characteristics of writing an uncovered index put option, well known for its nonlinear risk exposure. A small market decline will generate losses comparable to receiving the put premium, resulting in a flat performance during small market declines. When markets are rising, the profit will be somewhat similar to the received put premium. In these cases, the return can be seen as a market neutral investment strategy. The trouble arises when the market faces severe declines, erasing the put premium and generating potentially huge losses for the put-writer. Shlefer & Vishny (1997) documents that additional capital get more expensive following a negative price shock, this leads to an increased exposure to further shocks for hedge funds with arbitrage strategies. Brunermeier & Pedersen (2008) extends this research and argues that loss of liquidity to arbitrageurs produce asset price declines. These effects magnify the severe declines experienced by such option like strategies. This leads to the fact that risk-adjusted return measures such as the Sharpe Ratio may overestimate the hedge funds performance (Goetzmann, Ingersoll, Spiegel & Welch, 2004).

In the paper "The Cost of Capital for Alternative Investments" (2015) Jakub Jurek and Erik Stafford suggest that hedge fund investors specialize in bearing downside market risk. They further extend the research by Mitchell & Pulvino (2001) and Agarwal & Naik, (2004) and show in their research paper that a put-writing strategy on the S&P 500 index can account for the risk and return of the broad HFRI Fund Weighted Composite Index. With the knowledge of previous research

on the risk properties of hedge funds, we find motivation to apply a similar put-writing strategy to study the performance of Nordic hedge funds.

5.0 Methodology

To replicate the risk and return of the NHX we write short-dated put options on the S&P 500 index, (Jurek & Stafford, 2015). The portfolio is rebalanced monthly in accordance with the requirements set by the Chicago Option Board Exchange (CBOE) (Santa-Clara & Saretto, 2009). Our focus will be to match the drawdowns, the realized return volatility and the CAPM betas over the entire sample period. The importance of capturing the drawdowns is motivated by the potential nonlinearity in the underlying economic risk exposure. We consider a range of different strategies consisting of different levels of leverage (L) and the options strike price, e.g. the moneyness (Z) of the option. Due to the requirements of the CBOE, we will limit the leverage values to $L \in \{1, 2, 4, 6, 8, 10\}$. The moneyness of the option is determined by a fixed Z-value with $Z \in \{-1, -2, -3\}$. After the computation of the various strategies, we will select the strategy that most closely matches the characteristics of the NHX.

5.1 Strike Selection

The strategy writes a put option at a fixed strike Z-scores, where the option strike price is given by the equation:

$$K(Z) = S * \exp\left\{\left(r_f(\tau) - q(\tau) + \frac{\sigma^2}{2}\right) * \tau + \sigma(\tau) * \sqrt{\tau * Z}\right\} \qquad (7)$$

$r_f(\tau)$, $q(\tau)$ and $\sigma(\sigma)$ represent the risk free rate[7], the dividend yield[8] and the stock index volatility[9], respectively. The trade maturity, τ, will typically be one month due to the nature of the strategy. Since the option maturity date will generally not match the roll date, we select the contract with the nearest expiration date, T, after the roll date. We open our position at the end of each month, t_o, and close our position one month later, t_c. The trade maturity is set to $\tau = t_o - t_c$,

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[7] The risk free rate is acquired from the U.S Department of the Treasury, and reflects zero-coupon yield curves.
[8] The dividend yield is acquired from yahoo finance, and represents the aggregate dividend from the companies in the S&P 500 index.
[9] The stock index volatility is acquired from CBOE, represented by the VIX index.

equal one month, rebalancing the position on the last business day in the month. In order to measure the volatility on the one-month position, we use the CBOE implied volatility index (VIX).

5.2 Capital and Leverage Selection

Due to the requirements of CBOE, this strategy requires posting of equity. The equity represents the investor's capital in the position and carries the risk of losses due to fluctuations in marking-to-market value of the put option. The maximum loss the put-writer can experience is determined by the options strike price. This means that a put-writing strategy is fully funded in the sense of being able to guarantee the terminal payoff, if the investor posts the discounted value of the exercise price less the proceeds of the option sale:

$$k_A = e^{-r_f(T-t_o)*(T-t_o)} * K - P(K,S,T;t_o). \tag{8}$$

In practice, it is common that the investor posts equity of k_E, and broker posting the balance, k_D which works as debt. The interest is paid in form of a broker's haircut on the risk free rate on the investor's capital contribution. The leverage of the position is represented by the asset capital to investors equity ratio, $L = \frac{k_A}{k_E}$.

The monthly excess cash generated by the strategy is assumed to earn the risk-free rate less the broker's haircut, h. If the broker's haircut exceeds that of the risk-free rate, the deposit earns zero. We formulate the accrued interest payment as:

$$AI(t_o, t_c) = \left(\frac{k_A}{L} + P(K,S,T;t_o)\right) * (e^{\max(0,r_f(\tau)-h)} - 1). \tag{9}$$

5.3 Return on Strategy

At the end of each month, we perform three operations:

1. We invest the required capital determined by the desired leverage value in a one-month U.S treasury bill.
2. We close our short position from the previous month by buying back the option at the prevailing ask price.
3. We open our new short position by writing an option on the S&P 500 index and receive the prevailing bid price.

The strike price is given by the proposed strike price calculated by equation 1. These operations are continued each month over the entire sample period, rebalancing our portfolio at the last trading day of each month.

The investor's return on capital is affected by the change in the value of the put option and the accrued interest divided by the capital contribution:

$$r(t_o, t_c) = \frac{P(K,S,T;t_c) - P(K,S,T;t_o) + AI(t_t,t_c)}{k_E}. \tag{10}$$

5.4 Requirements from Chicago Board Options Exchange

The CBOE requires that the writer of the put option deposit equity as an insurance against market decline. The amount is determined by equation 5, which states that the investor must post equity equal to the option proceeds plus 15% of the current index level minus the amount of which the option is out of the money. The minimum amount of equity posted is the aggregated strike price.

$$\min K_e \, CBOE =$$

$$Max(0, 10 * K, P^{Bid}(K,S,T;t_o) + 0.15 * S - Max(0, S - K) \tag{11}$$

Concerning our strategy, the requirements of CBOE makes leverage values higher than 10 difficult to implement due to the need of external financing. In our model, we will therefore restrict the leverage values to range between 1 and 10.

5.5 Put-Writing Strategy Example

To demonstrate the strategy, we give an example where we open a position at January 31st, 2015 and close the position at February 28th, 2015. The strategy has leverage equal 1, and a fixed Z-value of -1, (L: 1, Z: -1). At January 31, the values of the CBEO Volatility Index (VIX) was at 20.97%, the risk free rate was at 0.01%, the S&P 500 index was at USD 1994.99, and the dividend yield was at 1.97%. Using equation (7), these key figures gives us a proposed strike price of USD 1882. The closest trading strike that expires 6th of March, was USD 1880, and by selling this option, we receive the prevailing option bid price of USD 15.9. Applying equation (8), we find the required capital we need to post for the strategy. At February 28th, we close our position by buying back the position with the same trading strike, maturing at 6th of March, at the prevailing ask price of USD 0.15. Using equation (9) we find the accrued interest from or posted capital, which gives us a monthly return in February of 0.85%, using equation (10).

Finally, we open our new position at 28th of February using new key figures, and continue the mechanic strategy over the entire sample period.

6.0 Results

The characteristics of the various put-writing strategies are summarized in table 3. Reporting the drawdown, the volatility and the CAPM betas along with an implied fee. The implied fee equalizes the compounded performance from the NHX net-of-fees and the compounded performance from the put-writing strategy. Since the NHX is reported net-of-fees, the implied fee is thought to represent the management fees taken by the hedge fund managers. Therefore, in order for the put-writing strategy to match the NHX pre-fee, the implied fee must be equal to- or greater than the historical hedge fund fees. The reported volatility is simply the standard deviation over the sample period without adjustments. To calculate the CAPM betas, we run the CAPM regression (3) on the entire sample. The CAPM betas from the various strategies are found in table 3.

6.1 Put-Writing Strategy Selection

The strategies we employ offer a wide range of different risk exposures, with different levels of moneyness of the option and degree of leverage. Holding the degree of leverage fixed, the riskiness of the strategy declines, as the Z-value increases in negativity. This is consistent with our intuition, considering that the Z-value determines how far the options are written out-of-the-money[10]. The possibility of losses declines as the options are written further out-of-the-money. When holding the Z-value fixed, the riskiness of the strategy increases with higher leverage[11]. This is also consistent with our intuition, as increased gearing is related to higher risk.

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[10] Strike price is given by the equation $K(Z) = S * \exp\left\{\left(r_f(\tau) - q(\tau) + \frac{\sigma^2}{2}\right) * \tau + \sigma(\tau) * \sqrt{\tau * Z}\right\}$ where the Z-value determines the moneyness of the option.

[11] The degree of leverage is determined by the equation $L = \frac{k_A}{k_E}$ where $k_A = e^{-r_f(T-t_o)*(T-t_o)} * K - P(K, S, T; t_o)$ and k_e is the posted equity.

From table 3, the reported volatility for most of the strategies are lower than the volatility experienced by the S&P 500 index. Another interesting finding is that most of the strategies would have "survived" throughout the entire sample period, meaning that despite market declines, the requirements from CBOE would have been fulfilled over the entire period. Even the highly leveraged strategies with leverage values up to eight fulfill the capital requirements.

The strategy that most closely matches the risk properties to the Nordic hedge fund index is the strategy with leverage of L: 1 and Z-value of Z: -1. The estimated maximum drawdown of -12.37% is a close fit with the maximum drawdown of the NHX at -11.28%. The reported CAPM beta and volatility also provide a good fit to the corresponding values of the NHX. In figure 3, the return performance of the strategy is shown as a graph, along with the performance of the NHX. In periods with severe market declines such as the financial crisis in 2008, the strategy accurately replicates the movements of the NHX. In less severe market declines such as in September 2011 and March 2015, the strategy also matches the performance of the NHX well. Figure 4 illustrates the drawdown for each month and the fit between the estimated results of our strategy and those of the actual the NHX. The overall fit during the entire sample period is consistent despite the change in market conditions for hedge funds and individual changes in hedge fund strategies.

Figure 3.
Cumulative return for NHX and put-strategy (L: 1, Z: -1)
The figures show the cumulative value of 100 NOK invested in the NHX net-of-fee, and the put-writing strategy (L: 1, Z: -1) from first of January 2006 to 31. December 2016 (144 months).
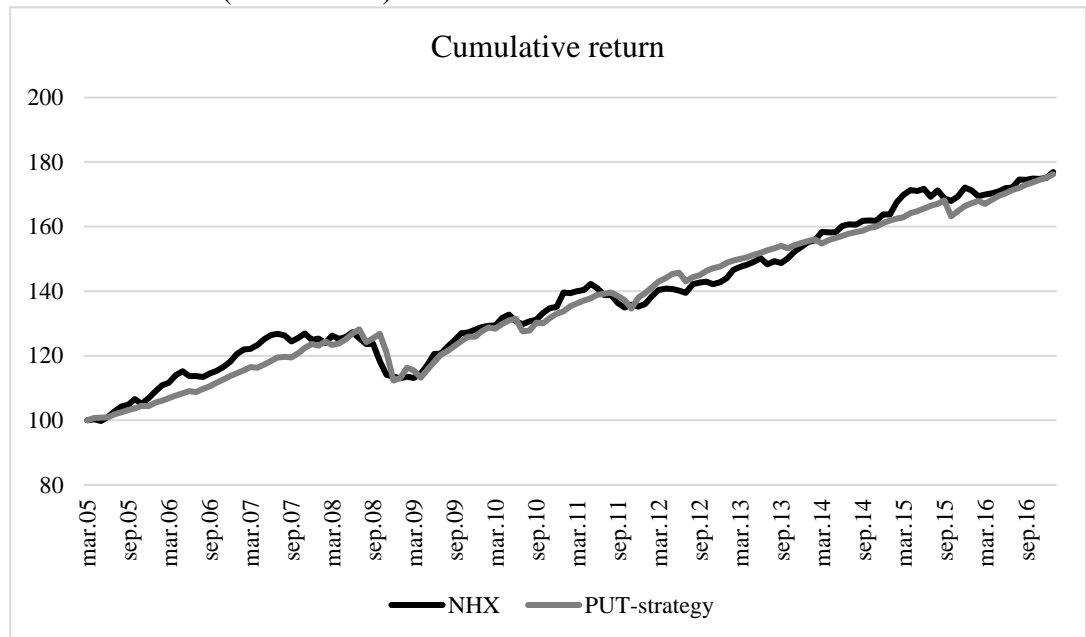

Figure 4.
Drawdown for NHX and Put-strategy (L: 1, Z: -1)
This figure shows the drawdown from the put-writing strategy (L: 1, Z :-1) and the drawdown from the NHX net of fees over the entire sample period. The maximum drawdown is experienced during the financial crisis in 2008 for both NHX and the put-writing strategy.
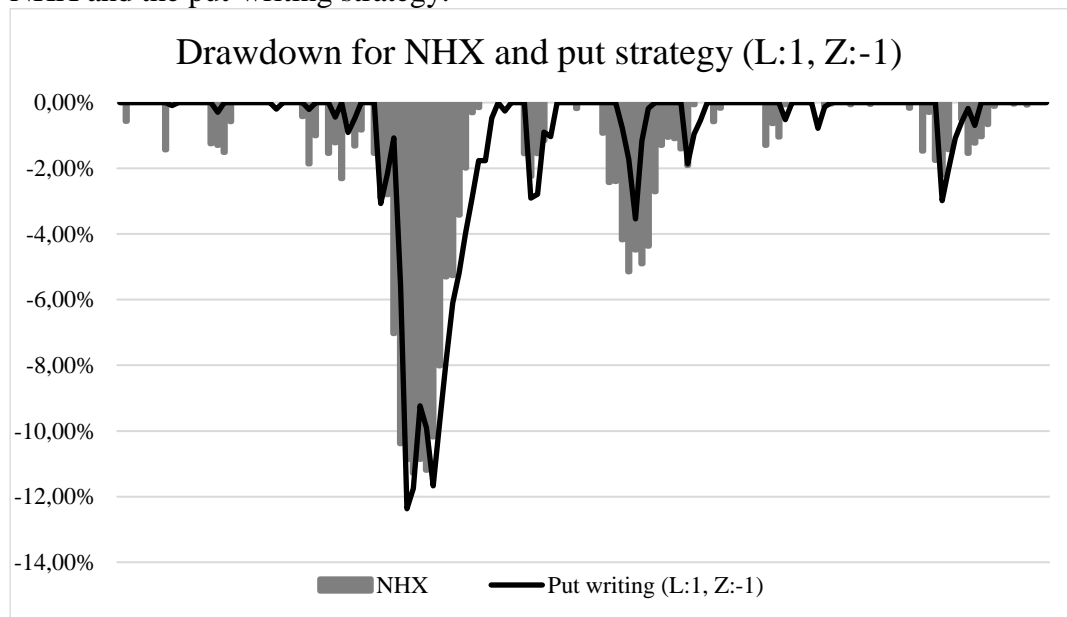
Finally, in order for the strategy to match the performance of the NHX, the results need to account for the fees taken by the hedge fund managers. Interestingly, the implied annual management fees from our strategy that provides the best fit is only 0.89 %. Ibbotson, et al. (2010) find in their study of hedge funds that the average annual all-in fee taken by the hedge funds in the TASS database between 1995 and 2009 is 3.43%. Jurek & Stafford (2015) find an average annual all-in fee of 3.8% in the period between 1996 and 2012. The difference between the implied fee from the strategy and the all-in-fee taken by the hedge funds is about 2.5 % annually.

6.2 Result Summary

Two observations can be made from the results from our put-writing strategy that are both interesting for further discussion:

- Firstly, the strategy appears to provide a close fit with the NHX *net-of-fees*.
- Secondly, the implied fee for the strategy with the closest fit is too low to account for the fees actually taken by the hedge fund managers.

Table 3.
Risk Properties of Put-Writing Strategy

Table 3 summarizes the maximum drawdowns, the quarterly volatility measured by standard deviation, and the CAPM beta of the various put-writing strategies. The implied fee is the annualized difference between the estimated cumulative return of the strategy and the NHX net of fees. The various strategies are defined by a fixed Z-score and leverage (L). Both the standard deviation and the CAPM betas are calculated using quarterly returns.

		$Z = -1$		
LEVERAGE (L)	DRAWDOWN	VOLATILITY	CAPM BETA	IMPLIED FEE
1	-12.37%	4.52%	0.23	0.89%
2	-25.61%	8.88%	0.46	5.37%
4	-48.82%	17.36%	0.91	17.36%
6	-67.16%	25.49%	1.35	20.54%
8	-80.91%	33.36%	1.78	26.51%
10	-90.64%	41.11%	2.20	30.58%

		$Z = -2$		
LEVERAGE (L)	DRAWDOWN	VOLATILITY	CAPM BETA	IMPLIED FEE
1	-5.25%	2.01%	0.08	-1.34%
2	-11.15%	3.81%	0.17	0.91%
4	-23.10%	7.51%	0.35	5.32%
6	-34.25%	11.17%	0.52	9.57%
8	-44.45%	14.76%	0.69	13.67%
10	-53.71%	18.28%	0.86	17.58%

		$Z = -3$		
LEVERAGE (L)	DRAWDOWN	VOLATILITY	CAPM BETA	IMPLIED FEE
1	-0.93%	0.95%	0.01	-2.38%
2	-2.31%	1.22%	0.04	-1.15%
4	-5.07%	2.09%	0.08	1.32%
6	-8.15%	3.08%	0.14	3.76%
8	-11.40%	4.12%	0.18	6.20%
10	-14.87%	5.18%	0.23	8.61%

7.0 Analysis

Analyzing hedge fund returns relative to the linear risk-factor models (CAPM, Fama-French/Carhart and Fung-Hsieh) and our simple put-writing strategy yields valuable insight of hedge funds risk exposure. Our results implies that traditional risk-factor models are inappropriate in order to explain the true risk exposure of hedge funds.

7.1 Traditional Risk-Factor Models and Put-Writing Strategy

In contrast to the traditional linear risk-factor models such as the CAPM, three-factor model and nine-factor model, our put-writing strategy matches the drawdown and net-of-fee returns of the NHX. The drawdown of the various factor models differs from the drawdown of the NHX, reported in figure 5, with greater losses during the financial crisis in 2008. Studying the cumulative returns in figure 6, the traditional linear risk-factor models consistently deliver lower returns than the NHX and the best fitting put-writing strategy. With different drawdown characteristics, and lower returns throughout the sample period, the traditional linear risk-factor models do not fully explain the risk-return profile of the NHX. However, our suggested, best fitting put-writing strategy, with leverage of L: 1, and Z-value of Z: -1 as reported in figure 6, provides the best replication of the risk and return profile of the NHX net-of-fees. This result supports our belief that Nordic hedge funds, along with other hedge funds, have a nonlinear risk exposure. These results imply that the traditional linear risk-factor models tend to underestimate the riskiness of Nordic hedge funds and that Nordic hedge fund managers specialize in bearing downside market risk, which the investors needs to be compensated for.

Figure 5.
Drawdown comparison for NHX and the factor models

The figure plots the monthly drawdown over the entire sample period (1. January 2006 to 1. January 2017) for each factor model, along with the drawdown for the NHX net of fees.
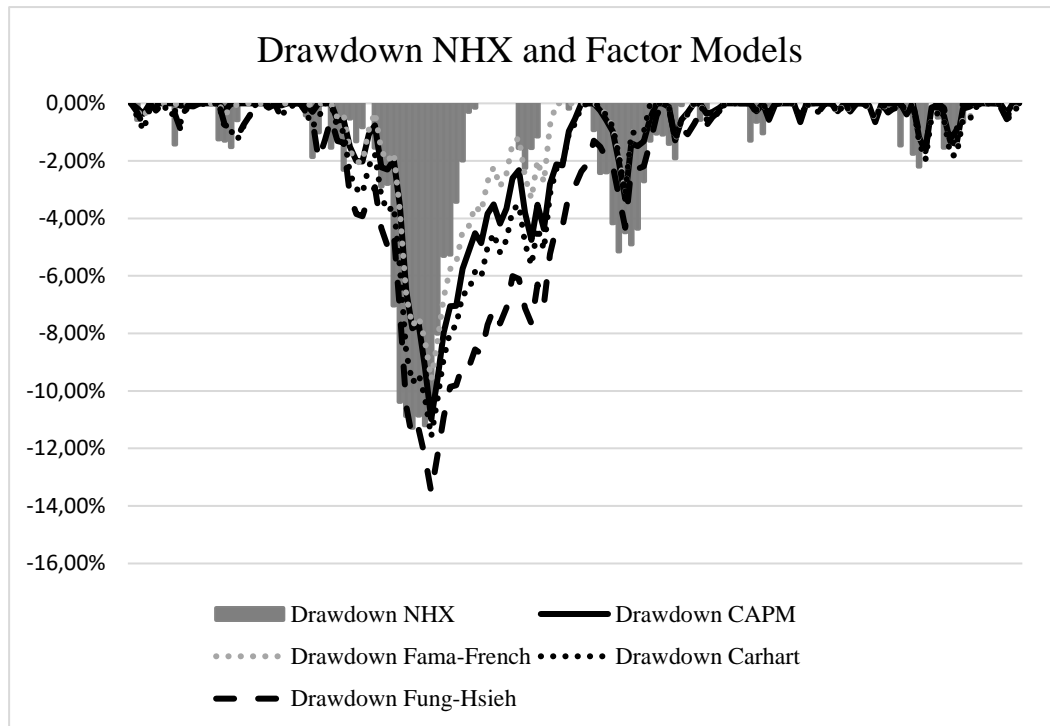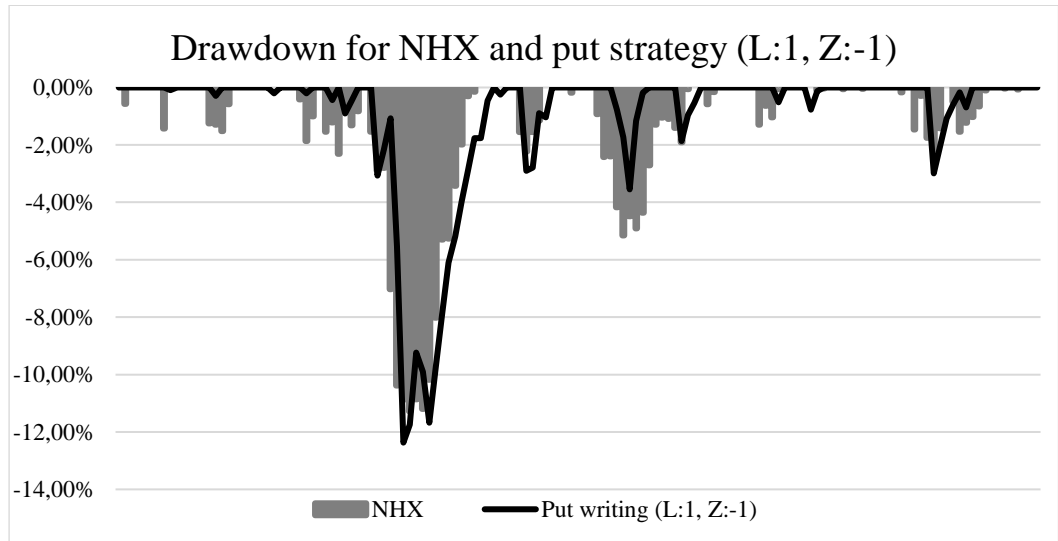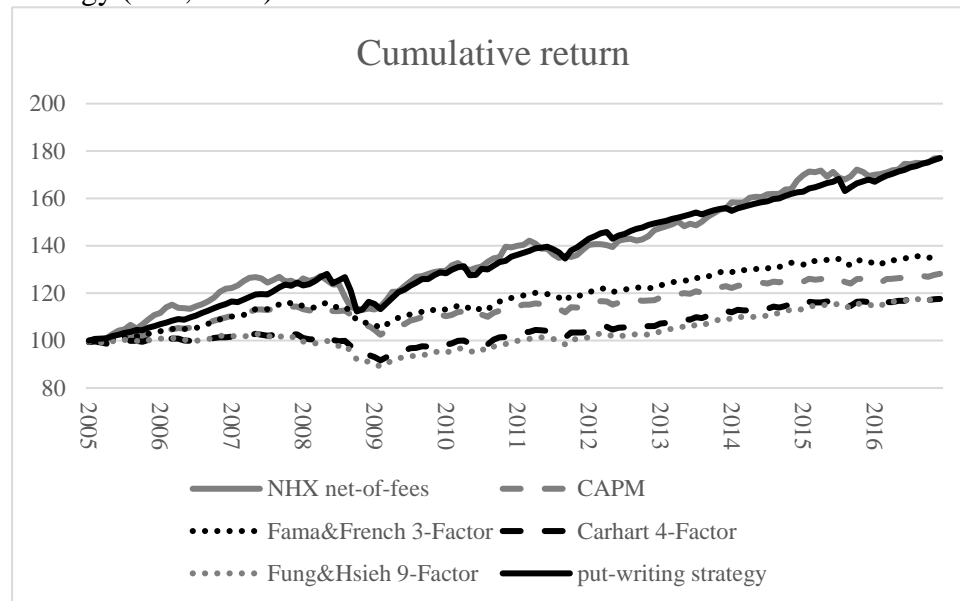

Drawdown for NHX and put strategy (L:1, Z:-1)

Drawdown NHX and Factor Models

Figure 6.
Comparative cumulative return

The figure plots the value of 100 NOK invested in January 2006 to January 2017 for the various factor models along with the NHX net of fees and the Put-writing strategy (L: 1, Z: -1).

The results of the put-writing strategy diverges from what could be expected based on the research of Jurek & Stafford (2015), in that our best fitting put-writing strategy (L: 1, Z: -1) is not able to account for the pre-fee returns of Nordic hedge funds. The difference between the compounded performance of NHX net-of-fees and the strategy is only 0.89% per year. Previous studies (Ibbotson, et al., 2010) and (Jurek & Stafford, 2015) all found that hedge fund managers typically require a fee that range between 3% and 4%, and our put-writing strategy are not able to account for that fee.

7.2 NHX and HFRI Performance

One interpretation of these results is that Nordic hedge fund managers are able to deliver an abnormal excess return of 2% to 3% with their investment strategies relative to the hedge funds incorporated in the HFRI. Comparing the NHX and the HFRI, which earlier studies has shown to be reminiscent of writing out-of-the money put options on the aggregate index (Jurek and Stafford, 2015), may be useful in order to understand why our put-writing strategy is unable to replicate the performance of the pre-fee NHX. In table 4, we compare descriptive statistics for the NHX and the HFRI. The NHX appears less risky compared to the HFRI, with both lower maximum drawdown and volatility. Moreover, with a higher

mean of yearly returns after fee, the NHX appears as a more attractive investment opportunity than the HFRI. This result could have three explanations:

- Firstly, that the NHX simply outperforms the HFRI and that Nordic hedge fund manager's is able to create a larger abnormal excess return than the funds incorporated in the HFRI.

- Secondly, the presence of hedge fund biases is stronger in the NHX than the HFRI.

- Finally, the NHX could be exposed to return smoothing in a larger degree than the HFRI.

Table 4.
Comparative descriptive statistics between NXH and HFRI

This table shows the yearly mean return, the volatility, measured by standard deviation, the maximum drawdown and the CAPM betas for both NHX and HFRI net of fees based on monthly observations from December 2005 to February 2017. The CAPM betas are the average of the quarterly betas extracted from the CAPM equation (1).

	HFRI net of fees	NHX net of fees
Mean	4.77%	4.99%
Volatility	6.10%	4.77%
Max. Drawdown	-21.42%	-11.27%
CAPM beta	0.37	0.25

7.4 Hedge Fund Biases

If there is significant presence of survivorship bias or backfill bias (Malkiel & Saha, 2005), the performance of Nordic hedge fund may be overestimated, and it would then be unlikely that the true risk is lower than the risk reported from the realized return; rather the opposite would be the case. A stronger presence of the above-mentioned biases could be a factor that evens out the performance of the NHX and the HFRI. From the studies of Horst & Verbeek (2007), Ackermann et. al. (1999), Fung & Hsieh (2000) and Malkiel & Saha (2005), the mentioned biases may cause a reduction in the mean return in hedge fund indices to over 6 percent annually.

Studying the reporting standards for the HFRI and the NHX, both indices have similar regulations to prevent biases. However, in contrast to the HFRI, the NHX does not have the same requirements to the length of trading for new funds, and the size of AuM[12] (HedgeNordic, 2017 & Hedge Fund Research, 2017). To be incorporated in the HFRI a fund must be actively traded for at least 12 month with complete trading history, and minimum $50 million in AuM. Together, these two differences in reporting standards could possibly give a larger degree of backfill bias for the NHX.

7.5 Return Smoothing

Moreover, other research on hedge fund returns suggests that managers may misreport their return by applying return smoothing during lock-up periods, when investors are not allowed to sell shares (Bollen & Pool, 2008). Return smoothing may cause investors to view the hedge fund as less risky because of the absence of extreme negative outcomes. This implies that with the presence of return smoothing, the actual drawdown of the NHX may be lower. Studying the various put-writing strategies, we find several strategies with return and risk exposure similar to the NHX, but with more dramatic declines during the financial crisis in 2008. If the hedge funds incorporated in the NHX exhibits return smoothing, these strategies could provide a good fit to the NHX, and also be able to account for the fees taken by the hedge fund managers.

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[12] To be included in the HFRI index, funds must have at least $50 Million under management or actively trading for at least twelve month.

8.0 Conclusion

In this paper, we show that the NHX apparently delivers statistical significant net-of-fees alphas between 3% and 4% yearly relative to commonly used risk-factor models such as the CAPM, Fama-French Three-factor model, Carhart Four-Factor model and Fung-Hsieh Nine-factor model. Extending the work of Mitchell & Pulvino (2001), Agarwal & Naik (2004), Lo (2001) and Jurek & Stafford (2015), we show that a mechanic put-writing strategy on the S&P 500 index is able to replicate the risk-return profile of Nordic hedge funds and match the net-of-fees returns of the NHX, but not the NHX pre-fee returns. This implies that the risk exposure of Nordic hedge funds is nonlinear, and hence, linear risk factor models are inappropriate in order to explain the performance of Nordic hedge funds. Furthermore, this result suggests that Nordic hedge fund managers on aggregate have been able to earn alphas, but not for the investors, because of the required hedge fund management fees. However, this result is critically dependent on two assumptions: Firstly, that there has been no return smoothing. Secondly, that there are no presence of survivorship bias and backfill bias in the NHX dataset. Even a small degree of return smoothing during the most critical months in the financial crisis in 2008 or a minor presence of the above-mentioned biases throughout the sample, could bias the results in the hedge fund managers' favor. If this were the case, the NHX pre-fee alpha could potentially be insignificant or even negative relative to the mechanic put-writing strategy.

9.0 References

Ackermann C., McEnally r. & D. Ravenscraft. (1999).The Performance of Hedge

Funds: Risk, Return, and Incentives. The Journal of Finance 54, pp. 833-874.

Agarwal, V., & Narayan, N. Y. (2004). Risks and portfolio decisions involving hedge funds. Review of Financial Studies 17, pp. 63-98.

Asness, C., Krail, R., & Liew, J. (2001). Do hedge funds hedge? Journal of portfolio Management 28, pp. 1-19.

Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. Journal of Political Economy 81, pp. 617-654.

Bollen, N. P., & Pool, V. K. (2009). Do hedge fund managers misreport returns? Evidence from the pooled distribution. Journal of Finance 64, pp. 2257-2288.

Brown, S., & J.F., S. (2006). Caught by the tail: Tail risk neutrality and hedge fund returns. Stern School of Business.

Brunnermeier, M. & Pedersen, L., H. (2009). Market liquidity and funding liquidity. Review of Financial Studies 22, pp. 2201–2238.

Charles, C., Farnsworth, G. V., Liang, B. & Lo, A. W. (2013). Liquidity costs, return smoothing, and investor flows: Evidence from a separate account platform. Working paper, MIT.

Carhart, M. (1997). On persistence in mutual fund performance. Journal of Finance 52, pp. 57-82.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, pp. 3-56.

Fama, E. F., & French, K. R. (2010). Luck versus skill in the cross-section of mutual fund returns. Journal of Finance 65, pp. 1915-1947.

French, K., (2008). Presidential address: The cost of active investing, Journal of Finance 58, pp. 1537–1573.

Fung, W., & Hsieh, D. A. (1997). The risk in hedge fund strategies: Theory and evidence from trend followers. The Review of Financial Studies 14.

Fung, W., & Hsieh. D. A. (2000). Performance Characteristics of Hedge Funds and Commodity Funds: NaturalVersus Spurious Biases. Fuqua School of Business Duke University.

Fung, W., & Hsieh, D. A. (2001). The risk in hedge fund Strategies: Theory and evidence from trend followers. Review of Financial Studies 14, pp. 313-341.

Fung, W., & Hsieh, D. A. (2004). Hedge fund benchmark: A risk based approach. Financial Analysts Journal 60, pp. 65-80.

Getmansky, M., A. Lo & I. Marakov. (2004). The life cycle of hedge funds: Fund flows, size and performance. Sloan School of Management.

Goetzmann, W., Ingersoll, J., Spiegel, M. & Welch, I. (2004). Sharpening Sharpe Ratios. Yale School of Management.

Hasanhodzic, J., & Lo, A. W. (2007). Can hedge fund returns be replicated? The linear case. Journal of Investment Management 5, pp. 5-45.

Huang, J., Liechty, J. & Rossi, M. (2012). Return Smoothing and its Implications for Performance analysis of Hedge Funds.

Horst, J. T. & Verbeek, M. (2007). Fund Liquidation, Self-selection, and Look-ahead Bias in the Hedge Fund Industry. Review of Finance, pp. 605-632.

Ibbotson, R. G., Chen, P., & Zhu, K. X. (2010). The ABCs of hedge funds: Alphas, Betas, and costs, working paper. Yale School of Management.

Jensen, M. C. (1986). Agency Cost of Free Cash Flow, Corporate Finance, and Takeovers. The American Economic Review, Vol. 76, No. 2, pp. 323-329.

Joenväärä, J., Kosowski, R., & Pekka, T. (2016). Hedge fund performance: What do we know? Centre for Hedge Fund Research.

Jurek, J. W., & Stafford, E. (2015). The cost of capital for alternative investments. The Journal of Finance 5, pp. 2185-2226.

Linter, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets, Review of Economics of Statistics, 47, pp. 13–37.

Lo, A. W. (2001). Risk management for hedge funds: Introduction and overview. Financial Analysts Journal 6, pp. 16-33.

Malkiel, B. G., & Saha, A. (2005). Hedge Funds: Risk and return. Financial Analysts Journal.

Mitchell M. & Pulvino T. (2001). Characteristics of Risk and return in Risk Arbitrage. The Journal of Finance 56, pp. 2135-2175.

Mossin, J. (1966). Equilibrium in a Capital Asset Market. Econometrica 60, pp. 768-783.

Patton, A. J. (2009). Are "market neutral" hedge funds really market neutral? Review of Financial Studies 22, pp. 2495-2530.

Santa-Clara, P. & Saretto, A. (2009) Option strategies: Good deals and margin calls. Journal of Financial Markets 12, pp. 391–417

Sharpe, W. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk, Journal of Finance 19, pp. 425–442.

Sharpe, William F. (1966). Mutual Fund Perfomrance. The Journal of Business 39, pp. 119–138

Shleifer, A. & Vishny, R. W. (1997). The limits of arbitrage, Journal of Finance 52, pp. 35–55.

Data sources:
CBOE (2017, January) Historical Put-Option Data.
https://datashop.cboe.com/optionsdata

Fama-French Three Factors/Carhart Four Factors. (2017, January).
http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research

Fung-Hsieh Trend-Follow Risk Factors. (2017, January)
https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm

HedgeNordic (2017, January), NHX dataset and Nordic Hedge Fund information.
http://nhx.hedgenordic.com/Login.aspx?ReturnUrl=%2f%3fpageid%3d61&pageid=61

HedgeNordic, (2017, June) NHX reporting standards
http://www.nhx.hedgenordic.com/?pageid=20

Hedge Fund Research (2017, June), HFRI information.
https://www.hedgefundresearch.com/

Hedge Fund Research (2017, June), HFRI reporting standards.
https://www.hedgefundresearch.com/sites/default/files/pdf/HFRI_formulaic_methodology.pdf

U.S Department of The Treasury. (2017, January). *treasury.gov.* Acquired from Treasury Yield Curve Rates:
 https://www.treasury.gov/resource-center/data-chart-center/interest-rates/Pages/TextView.aspx?data=yield

Yahoo Finance. (2017, January). *Yahoo.com.* Acquired from Yahoo Finance:
https://finance.yahoo.com/quote/%5Egspc?ltr=1

Yahoo Finance. (2017, January). *Yahoo.com.* Acquired from Yahoo Finance:
https://finance.yahoo.com/quote/%5Evix?ltr=1

10. Appendix

10.1 Descriptive statistic – NXH net of fees and S&P500

Table 5: Descriptive statistics of NHX with S&P 500 in comparison

Sample: 2005M01 2016M12

	NHX	S_P_500
Mean	0.004222	0.005123
Median	0.004900	0.010236
Maximum	0.033100	0.107723
Minimum	-0.043500	-0.169425
Std. Dev.	0.011264	0.041033
Skewness	-0.816938	-0.748757
Kurtosis	5.213779	5.017972
Jarque-Bera	45.42220	37.88855
Probability	0.000000	0.000000
Sum	0.607981	0.737752
Sum Sq. Dev.	0.018143	0.240775
Observations	144	144

10.2 Factor correlation

Table 6: Factor correlation for CAPM, Fama-French/Carhart and Fung/Hsieh

	MKT_RF	SMB	HML	MOM
MKT_RF	1.000000	0.387202	0.294122	-0.350922
SMB	0.387202	1.000000	0.133775	-0.108094
HML	0.294122	0.133775	1.000000	-0.419212
MOM	-0.350922	-0.108094	-0.419212	1.000000

	S_P_500	SIZE_SPREAD	_10YRS_TR...	CREDIT_SP...	PTFSBD
S_P_500	1.000000	0.372683	-0.059816	-0.004560	-0.367625
SIZE_SPREAD	0.372683	1.000000	-0.039484	0.047222	-0.110116
_10YRS_TR...	-0.059816	-0.039484	1.000000	-0.927641	-0.000250
CREDIT_SP...	-0.004560	0.047222	-0.927641	1.000000	0.011555
PTFSBD	-0.367625	-0.110116	-0.000250	0.011555	1.000000
PTFSCOM	-0.192790	-0.083663	-0.165058	0.176699	0.228151
PTFSFX	-0.280262	-0.035675	-0.048642	0.133089	0.462438
PTFSIR	-0.325315	-0.088841	-0.091123	0.177349	0.196390
PTFSSTK	-0.288713	-0.084296	-0.121527	0.200070	0.181463

10.3 Distortions in regression Analysis

The regression analysis are supplemented with statistical tests in order to verify that the regression outputs are reliable. With the use of hedge fund indices, we encounter various distorting effects, which we need to correct for.

Serial correlation

Due to illiquid exposure and smoothed returns, Getmansky et. al. (2004) finds that hedge funds are likely to exhibit serial correlation in their returns. With the presence of serial correlation, the standard deviation will be underestimated, and the evaluation of the risk-return characteristics of the NHX may be wrongful.

Table 7: Durbin-Watson statistics of the NHX, CAPM

Dependent Variable: NHX
Method: Least Squares
Date: 08/07/17   Time: 08:57
Sample: 2005M01 2016M12
Included observations: 144

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003093	0.000696	4.443015	0.0000
MKT_RF	0.181742	0.016347	11.11773	0.0000

R-squared	0.465370	Mean dependent var		0.004222
Adjusted R-squared	0.461604	S.D. dependent var		0.011264
S.E. of regression	0.008265	Akaike info criterion		-6.739827
Sum squared resid	0.009700	Schwarz criterion		-6.698579
Log likelihood	487.2675	Hannan-Quinn criter.		-6.723066
F-statistic	123.6040	Durbin-Watson stat		1.999420
Prob(F-statistic)	0.000000			

In order to check for serial correlation, we run the Durbin-Watson test in Eviews. All of the regressions display only minor serial correlation, with test statistics from 1.88 (9-Factor model) to 1.99 (CAPM). A test statistic of 2 implies no serial correlation, and we do not do any further adjustment to our dataset.

Heteroskedasticity

Heteroskedasticity refers to the existence of differences in the standard deviation of a variable, experienced over a specific amount of time (Brooks, 2014). Related to our case, it refers to the possibility that the volatility in hedge fund returns changes over time. With the presence of heteroskedasticity, we might underestimate the error term in our coefficients.

Figure 8: Breusch-Pagan-Godfrey test for Heteroskedasticity, CAPM

Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	3.345688	Prob. F(1,142)	0.0695
Obs*R-squared	3.314712	Prob. Chi-Square(1)	0.0687
Scaled explained SS	5.056938	Prob. Chi-Square(1)	0.0245

As shown in the figure above, our dataset displays sign of heteroskedasticity but only for the 1%-level. As we are able to reject the null-hypothesis at a 5%-level, we choose to not do any further actions. Alternatively, would be to run regression with (semi)robust standard errors.

Non-stationarity

We want to check if the NHX is a stationary series, if the series is stationary we have a constant mean, constant variance and constant auto covariance. In a stationary series, a change or unexpected change in the series will gradually fade away. If the NHX is a non-stationary process, the series could be distorted by trends, cycles, random walks or a combination of all three. This could influence the statistical properties of the NHX and hence lead to spurious regressions, permanent change and that the t-ratio does not follow the t-distribution, which again leads to an inaccurate conclusion. We run the Augmented Dickey-Fuller test in order to control for non-stationarity. The null-hypothesis is non-stationarity.

Table 9: Augmented Dickey-Fuller test for non-stationarity

Null Hypothesis: NHX has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.268237	0.0000
Test critical values:	1% level	-4.023506	
	5% level	-3.441552	
	10% level	-3.145341	

*MacKinnon (1996) one-sided p-values.

The results from the Augmented Dickey-Fuller suggests that we can reject the null-hypothesis and that the NHX is a stationary series.

Multicollinearity

Multicollinearity occur when two or more explanatory variables in one of the multifactor models are highly correlated. Multicollinearity reduces the predictability of the affected risk factor because the risk factors linearly predicts one another. In order to test for multicollinearity in our multifactor models, we run a test for variance inflation factors (VIF-test). If the variance inflation factors indicator exceeds 5, there is a possibility of multicollinearity in our multifactor models.

Table 10: Variance Inflation Factors (VIF) for the various factors

Variance Inflation Factors
Date: 08/07/17   Time: 10:19
Sample: 2005M01 2016M12
Included observations: 144

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	4.78E-07	1.026206	NA
MKT_RF	0.000356	1.386327	1.356833
SMB	0.001067	1.181840	1.179140
HML	0.000867	1.253321	1.252253
MOM	0.000279	1.305375	1.305264

Variance Inflation Factors
Date: 08/07/17   Time: 10:19
Sample: 2005M01 2016M12
Included observations: 144

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	5.13E-07	1.127083	NA
S_P_500	0.000407	1.517631	1.494175
SIZE_SPREAD	0.000869	1.176478	1.171999
_10YRS_TREASURY...	5.49E-05	1.055718	1.055671
PTFSBD	2.89E-05	1.432722	1.381693
PTFSFX	1.79E-05	1.502082	1.498458
PTFSCOM	2.38E-05	1.261262	1.261258
PTFSIR	6.47E-06	1.313065	1.304599
PTFSSTK	2.83E-05	1.379171	1.263287

The results show that there are no presence of multicollinearity in neither of the multifactor models (CAPM, Fama-French/Carhart or Fung-Hsieh).

10.4 Tables

Table 11
Table 11 summarizes the annual returns for the NHX *net of fees,* SP500 and the put-writing strategy with leverage of 1, and Z-value of -1. The returns for 2005 includes Q2-Q4. The annual returns are calculated using the monthly returns.

	NHX *net of fee*	**SP500**	**Put-Writing Strategy (L:1,Z:-1)**
2005	9 %	6 %	5 %
2006	11 %	14 %	9 %
2007	4 %	4 %	7 %
2008	-11 %	-35 %	-7 %
2009	14 %	23 %	13 %
2010	8 %	13 %	5 %
2011	-3 %	0 %	4 %
2012	7 %	16 %	6 %
2013	8 %	30 %	5 %
2014	5 %	11 %	4 %
2015	5 %	-1 %	3 %
2016	3 %	10 %	5 %

Table 12
Table 12 summarizes the yearly return for the respective factor models. The returns are obtained using the monthly returns from January 2005 to December 2016. The regressions used for each model are found in equation 3-6.

	CAPM	**3-Factor**	**Carhart**	**9-Factor**
2005	3 %	3 %	0 %	0 %
2006	6 %	6 %	1 %	2 %
2007	4 %	6 %	1 %	0 %
2008	-7 %	-7 %	-9 %	-10 %
2009	5 %	6 %	5 %	5 %
2010	3 %	4 %	4 %	4 %
2011	0 %	1 %	1 %	1 %
2012	3 %	3 %	3 %	2 %
2013	5 %	6 %	6 %	7 %
2014	2 %	2 %	2 %	3 %
2015	0 %	1 %	1 %	2 %
2016	2 %	1 %	1 %	2 %

Table 13

Table 13 summarizes the yearly *net-of-fee* alphas for the factor models. The returns are obtained using the monthly returns from January 2005 to December 2016. The regressions used for each model are found in equation 3-6.

	CAPM	3-Factor	Carhart	9-Factor
Yearly Net-of-fees alpha	2.98%	3.74%	3.74%	3.7%
T-stat.	3.49	4.46	4.42	4.27
P. Value	0.006487	0.001666	0.0019	0.0035

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Preliminary Thesis Report

-An Examination of the Risk-Return Profile of Nordic Hedge Funds –

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Introduction

In 1990, Hedge Fund Research (HFR) estimated total assets under management (AUM) by hedge funds to $39 billion. In 2015, HFR estimated AUM of hedge funds to amount to more than $2.97 trillion (Agarwal, Mullally & Naik, 2015). In the same period, the number of active hedge funds grew from 610 in 1990 to over 10,000 in 2015. As for the number of hedge funds in Nordic countries, the number of hedge funds grew from just a limited number of hedge funds in 1996 to 155 hedge funds in 2016.

Given the global rapid growth of hedge funds and the amount of assets under management, it has become more important and interesting to evaluate and examine the performance of hedge funds. In 2005, the number of papers on hedge funds published in the premier finance journals (Journal of Finance, Journal of Financial Economics, Review of Financial Studies and Journal of Financial Quantitative Analysis) where only 16, but since 2005, the four journals has collectively published over 100 papers on hedge funds.

Hedge funds as an asset class has been widely debated over the years. Some argue that hedge funds contribute to market efficiency by locating mispriced assets. In addition, hedge funds have huge amounts of assets under management, which means that they can have a positive impact on corporate governance. Furthermore, hedge funds have access to a broad investment opportunity set, which implies the possibility of a diversifying effect for investors and flexibility in the hedge funds strategies. There is no doubt that some investors have made a lot of money by investing in hedge funds over the years. Critics of hedge funds argue that the hedge fund managers are overcompensated with fixed fees of 2% and performance fees of up to 20%. There are also several issues when evaluating hedge fund performance and contributions to the market. For instance, hedge funds are not obliged to report any of their activities, making alternative investments a black box, and it is hard to conclude if hedge funds as an asset class are successful or not. Lastly, we do not know if hedge funds actually contribute to an efficient market or if they just simply ride the bubbles.

Regarding earlier studies done on hedge fund performance, traditional linear risk factor models such as the capital asset pricing model (CAPM), Fama – French three-factor model, Carhart four-factor model and Fung-Hsieh nine-factor model all imply that hedge funds performed pre-fee alphas of 6% to 10% per annum over the period 1996 to 2012. If investors on average do not outperform the market

over time, how are the hedge fund managers able to perform such significant alphas? In order to capture the true risk, some argues that it is more appropriate to apply alternative methods. In the paper "The Cost of Capital for Alternative Investments", Jakub W. Jurek and Erik Stafford (2015) suggest that the equal weighted HFRI Fund Weighted Composite Index risk exposure can be replicated using a non-linear put-writing strategy on the S&P 500 Index.

In the present Master Thesis, we aim to provide a greater understanding of the cost of capital of Nordic hedge funds, by applying the put-writing strategy suggested by Jurek and Stafford. More specifically, we want to investigate if the findings of Jurek and Stafford (2015) also apply for the Nordic Hedge Index Composite (NHX). This leads to the research question: Is the cost of capital for Nordic hedge funds accurately matched by a single put-writing strategy?

Our paper consists of four parts, starting by a review of the existing literature relevant for our study. Next, we present the relevant theory before explaining the methodology used when examining the performance of Nordic hedge funds. Finally, we present the obtained literature we will apply in our assignment.

Literature review

The performance of hedge funds has been widely debated over the years, and there has been done a significant amount of research on the topic. The traditional linear factor regressions such as CAPM, Fama-French three-factor model and Fung-Hsieh nine-factor model have all been used to examine the returns of hedge funds. The previous research reveals that on average, hedge funds manage to deliver superior risk-adjusted performance over the sample period from 1994 to 2012 (Joenväärä, Kosowski, & Pekka, 2016). Using the standard CAPM to determine hedge fund returns, the previous research estimates average excess returns, alpha, between 6% and 10% per annum (Jurek & Stafford, 2015). In addition, Fung and Hsieh's nine-factor model reports an alpha of 4% (Fung & Hsieh, Hedge fund benchmark: A risk based approach, 2004). These results suggests market inefficiency and the possibility that hedge fund managers manage to outperform the market over time.

To explain the apparently appealing results, researchers have introduced several possible reasons. A report written by Burton G. Malkiel and Atanu Saha in 2005, called Hedge Funds: Risk and Return, describes the possible different biases that can occur in hedge fund returns.

A well-known explanation is the theory of backfill bias in reported hedge fund returns (Malkiel & Saha, 2005). Unlike mutual funds, hedge funds has no obligation to provide database publishers with information of their performance. Newly founded hedge funds often start reporting their results at a later point in time, and does only report their results if the results are satisfactory. The most favorable results are "filled back" to the database, which is called backfill bias, and leads to improved results for hedge fund indices. Estimates on backfill bias have showed that the returns between a normal portfolio and an adjusted "non-backfill bias" portfolio is on average 1.4 percentage points yearly (Fung & Hsieh 2001).

Another bias hedge fund indices may suffer from is "survivorship bias", and focus on the fact that previous existing hedge funds ("dead funds") are not included in the dataset. This gives a dataset only containing successful funds, and hence causes an upward biased sample, and a historical risk that is downward biased relative to the total hedge fund universe. From the research of Malkiel the estimated survivorship bias is estimated to be 0.5 percentage points per year. Other researchers have estimated the survivorship bias to be as large as 3 percentage points per year.

In addition to dataset biases, researchers have questioned if the traditional linear factor models are appropriate to use when studying the performance from hedge funds. The typical regression like CAPM and other traditional factor models can be viewed with the model:

$$Hedge\ fund\ return = Alpha + Risk\ free\ rate + \sum beta_i * factor_i$$

Most of the models use a multitude of traditional market factors. Researchers however have found that hedge fund managers typically take a lower exposure to traditional market factors, such as global bond and stock indices, slope of treasury yield curve and change in investment grade credit spreads. In recent research, authors have examined alternative replication strategies, which abandon traditional factor models.

Two researchers that have studied the performance of hedge funds over several decades are William Fung and David A. Hsieh. One of their first reports on hedge fund performance was the report from 1997, called Performance Characteristics of Hedge Funds and Commodity Funds: Natural Versus Spurious Biases, which documents that hedge fund managers typically employ dynamic hedging strategies

that have similarities to option returns. The traditional linear models do not capture the non-linear return and may therefore not be the appropriate tool to use. Studies on the distribution of hedge fund returns conclude that hedge funds have relatively low skewness and high kurtosis (Brown & J.F., 2006). As found in Fung and Hsieh study from 2001, The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers, hedge fund returns have similarities to options returns with apparently no systematic risk. This could possibly cause investors to conclude erroneously that there is no systematic risk. As a solution, Fung and Hsieh extract style factors from a broad sample of hedge fund returns. These style factors explain the relationship between return of hedge fund strategies and observed market prices. The style factors have similarities to options while they are uncorrelated with standard assets benchmarks. To get a good understanding of the risk, the non-linear relationship between the style factors and the market that the hedge funds trades in, must be modeled. This is however a difficult task, as most hedge funds do not disclose this information publicly.

An alternative approach to measure the required rate of return was presented by Jakub W. Jurek & Erik Stafford in "The Cost of capital for Alternative Investments" (2015). Instead of studying the risk for individual hedge funds, the aggregated risk property of the overall asset class is examined. The paper aims to replicate the risk profile of hedge funds using a simple index put option writing strategy. Based on this strategy, they are able to determine appropriate required rates of return, as a function of investor risk preferences and the underlying distribution of market returns (2015).

In the article, the performance of the hedge funds is studied using the Dow Jones Credit Suisse Broad Hedge Fund Index (DJSC), and the HFRI Fund Weighted Composite Index. In order to evaluate the required return, the researchers place focus on matching the drawdown in hedge fund indices during recessions and matching the realized return volatility and CAPM betas.

Examining the research done on Nordic hedge funds, we find little information. Nordic hedge funds have experienced increased attention and volume growth over the last years. In the Hedge Nordic database, we find 155 active hedge fund in the NHX Composite index. In comparison, we find 126 funds in the same index for 2011. The first Nordic Hedge Fund index was incepted in 1996, thus with a limited number of funds. Regarding Nordic hedge funds, the challenge is to find historical data that exist over a longer period of time.

We have found several smaller studies that examines hedge fund performance in Sweden and Denmark. The various methods that are being used are linear regression models such as CAPM, Fama & French three-factor model and Carhart's four-factor model. It seems to us that none of the earlier studies has been using non-linear models examining Nordic hedge fund returns. Since hedge funds are not obliged to publish strategies and market exposure, the difficulty arises when we try to examine single hedge fund performance.

Given the limited number of studies on Nordic hedge funds, we find it interesting to study the cost of capital for alternative investments for Nordic hedge funds. Previous studies have questioned the use of linear risk-factor models when examining hedge fund performance. This motivates us to use the method described by Jakub W. Jurek and Erik Stafford in 2015. The method involves studying hedge fund performance on an aggregate level, and it potentially removes the difficulties regarding limited data information of hedge fund strategies.

Theory

Risk and return concepts based on traditional linear risk factor models suggest that there is a linear relationship between risk and return. In practice, these models aim to provide cost of capital measures and risk adjusted returns, which can be used to decide whether an investment is profitable given the appropriate opportunity. In this part, we aim to explain the traditional theoretical framework applied to measure performance such as Sharpe ratio and Jensen's alpha, based on the single factor model CAPM. Further, we will define the multi factor models introduced by Fama & French (1992), Carhart (1997) and Fung Hsieh (2001).

The Sharpe ratio is a measure of risk and return, which is widely used to rank investment opportunities based on historical performance. The Sharpe ratio:

$$SR_i = \frac{E[R_i] - r}{\sigma_i} \tag{1}$$

Where SR_i is the Sharpe ratio, $E[R_i]$ is the expected return of portfolio i, r is the risk-free rate and σ_i is the volatility of portfolio i.

Jensen's alpha is another performance measure, represented by the intercept from the following regression:

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + \varepsilon_{it}. \tag{2}$$

Where $\beta_i = \frac{COV[R_p, R_m]}{VAR[R_m]}$

$R_{it} - R_{ft}$ represents the excess returns from portfolio i at the time t, $(R_{mt} - R_{ft})$ is the markets risk premium, β_i measures the portfolio's volatility relative to the market, ε_{it} is the error term of the regression and α_i is the intercept which says something about if the portfolios has outperformed the market.

Arbitrage Pricing Theory (APT) was suggested as an alternative to the CAPM by Stephen Ross (Ross, 1976). The APT suggests that the expected return for a given portfolio, i, is explained by multiple risk factors, not only the β, suggested by the CAPM. The APT is given by the following equation:

$$R_{it} = \alpha_i + \sum_{j=1}^{k} b_{ij} F_{jt} + \varepsilon_{it} \qquad (3)$$

From equation (3) the return of portfolio i is explained by a set of k factors F_{jt} which are common factors of systematic risk for all funds. β_{ij} represents the factor loadings and are specific to each portfolio. It is the F_{jt} and it's loadings that determine the expected return of portfolio i.

Based on the factor principle from the APT framework, Eugene Fama and Kenneth R. French defined a three-factor model, equation (4), in order to better explain the cross-sectional variation of stock returns. The three factor model is given by:

$$R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{iSMB}SMB_t + \beta_{iHML}HML_t + \varepsilon_{it} \qquad (4)$$

SMB (Small minus big), represents the return of a portfolio consisting of small stocks in excess of return on a portfolio consisting of large stocks. High minus low (HML) represents the return of a portfolio of stocks with a high book-to-market ratio in excess of the return on a portfolio consisting of stocks with a low book-to-market ratio. The β's represent the portfolios sensitivity to their respective risk factors.

Carhart's four-factor model (Carhart, 1997) is an extension to the Fama & French three-factor model where the momentum factor (MOM) is added.

$$R_{it} - R_{ft} = \alpha_i + \beta_{im}(R_{mt} - R_{rf}) +$$
$$\beta_{iSMB}SMB_t \beta_{iHML}HML_t + \beta_{iMOM}MOM_t + \varepsilon_{it} \qquad (5)$$

The momentum factor (MOM) represents the return of a portfolio consisting of positive momentum stocks in excess of return on a portfolio consisting of stocks with negative momentum.

William Fung & David A. Hsieh suggest that hedge fund trading strategies have option-like returns. They argue that in order to determine the cost of capital for

alternative investments, one should apply a non-linear strategy. They introduce two trading strategies, "Primitive Market-Timing Strategy" (PMTS) and "Primitive Trend-following Strategy" (PTFS). The PMTS strategy assembles the traits of an at-the-money standard straddle, and the PTFS have similar payouts as a "lookback straddle". The PMTS aims to capture the price movements on an underlying asset's initial price and closing price. PTFS aims to capture largest price movements achieved over a time interval.

Fung & Hsieh further argue that these properties can be added to the traditional linear risk-factor models in order to explain the cost of capital for alternative investments. They hence suggests a nine-factor model: $R_{i,t} = \alpha_i + \beta_{i,MKT}MKT_t + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,MOM}MOM_t + \beta_{i,\Delta 10Y}\Delta 10Y_t + \beta_{i,\Delta CredSpr}CredSpr_t + \beta_{i,BDTF}BDTF_t + \beta_{i,FXTF}FXTF_t + \beta_{i,CMTF}CMTF_t + \varepsilon_{i,t}$

The added terms $\Delta 10Y$ and $\Delta CredSpr$ represent the monthly change in US federal reserve 10-yr constant maturity yield, and the monthly change in the difference between Moody's BAA yield and the 10-yr constant maturity yield, respectively. The BDTF is the Fung-Hsieh bond trend-following factor measured as the return of PTFS bond lookback straddle. Further, FXTF is Fung-Hsieh currency trend-following factor measured as the return of PTFS currency lookback straddle. Lastly, CMTF is Fung-Hsieh commodity trend-following factor measured as the return of PTFS lookback straddle.

This research implies that one cannot obtain a higher return without taking on a higher degree of risk. Efficient Market Hypothesis states that it is not possible to beat the market over time because all stock prices already reflects all relevant information. This means that investors cannot buy underpriced or sell overpriced stocks. However, the Nordic Hedge Index Composite (NHX) outperforms the market year after year with a lower measured volatility. There could be several reasons for this, and some observers argue that hedge fund indexes report better risk-return ratios because of backfill and survivorship bias. Backfill bias occurs because hedge funds are not obligated to report any results, which leads only the successful hedge funds to report their results. Survivorship bias in the hedge fund index occurs because only the profitable hedge funds continue to report, and the hedge funds that are unsuccessful or are closed down, discontinue reporting.

Methodology

Empirics suggest that hedge funds are not market-neutral. For example, hedge funds suffer severe losses during extreme market events, such as the credit crisis in 2008, and perform extremely well in times when the economy is strong, such as during the boom years. Jakub W. Jurek and Erik Stafford (2015) suggest that an out-of-the-money put-writing strategy on the aggregate index reminiscent the downside risk exposure of hedge funds as an asset class. Bear markets render the option to expire in-the-money, which generates losses for the put writer, mild market declines results in flat performance of the put-writing strategy and bull markets leaves the option expiring out-of-the-money which yields the put option writer a profit.

In order to replicate the aggregate risk exposure for the Nordic Hedge Index Composite, we use the strategy described by Jakub W. Jurek and Erik Stafford (2015) in the paper "The Cost of Capital for Alternative Investments", where they write naked put options on the S&P 500 Index. The strategies are short dated and the portfolio is rebalanced monthly. Our focus will be to match the market drawdowns during the credit crisis in 2008, further; we are aiming to match the realized return volatility and CAPM betas. The importance of capturing the drawdowns is motivated by the potential non-linearity in the underlying economic risk exposure. We consider a range of different strategies consisting of different levels of leverage and the moneyness of the option. When we have identified the strategy comprising these requirements, we will examine the risk and return over the sample period.

Strike Selection

The strategy writes a put option at a fixed strike Z-scores, which Z is given by:

$$K(Z) = S * \exp\left\{\left(r_f(\tau) - q(\tau) + \frac{\sigma^2}{2}\right) * \tau + \sigma(\tau) * \sqrt{\tau * Z}\right\}$$

Where $r_f(\tau)$, $q(\tau)$ and $\sigma(\sigma)$ represent risk free rate, dividend yield and stock index volatility, respectively, corresponding to the trade maturity, τ. Since the option maturity date will generally not match the roll date, we select the contract with the nearest expiration date, T, following the roll date. We distinguish the trade initiation date, t_o and the trade closing date, t_c and the option expiration date, T. The trade maturity is set to $\tau = t_o - t_c$, equal one month, rebalancing the position on the last business day in the month. In order to measure the volatility on the one-month position, we use the CBOE VIX implied volatility index.

Capital and Leverage

This strategy requires posting of capital. The capital represents the investor's equity in the position and bears the risk of losses due to changes in marking-to-market value of the liability. The maximum loss the put-writer can incur is given by the options strike price. This means that a put-writing strategy is fully funded or unlevered in the sense of being able to guarantee the terminal payoff, if and only if the investor posts the discounted value of the exercise price less the proceeds of the option sale, $k_A = e^{-r_f(T-t_o)*(T-t_o)} * K - P(K,S,T;t_o)$. In practice, it is common that the investor posts equity of k_E, and broker posting the balance, k_D which works as debt. The interest is paid in form of a haircut on the risk free rate on the investor's capital contribution. The leverage of the position is represented by the asset capital to investors equity ratio, $L = \frac{k_A}{k_E}$.

The monthly excess cash generated by the strategy is assumed to earn the risk-free rate less the broker's haircut, h. If the broker's haircut exceeds that of the risk-free rate, the deposit earns zero. We formulate the accrued interest payment as: $AI(t_o, t_c) = \left(\frac{k_A}{L} + P(K,S,T;t_o)\right) * (e^{\max(0,r_f(\tau)-h)} - 1)$. The investor's return on capital is affected by the change in the value of the put option and the accrued interest divided by the capital contribution: $r(t_o, t_c) = \frac{P(K,S,T;t_c) - P(K,S,T;t_o) + AI(t_t,t_c)}{k_E}$.

Return on naked put writing

On the last trading day of each month from December 2004 throughout September 2016, we invest the investor's capital in a one-month U.S treasury bill and write an option on the S&P 500 index corresponding to the strike at Z-score, Z, receiving the bid price. The amount of posted capital, k_E, relative to the total exposure, k_A, determines the leverage, L, of the strategy as described before. The portfolio is rebalanced monthly by buying back last month's option at the prevailing ask price, and writing a new put on the index at the strike K(Z), receiving the bid. We consider strategies $[Z, L]$ with $Z \in \{-1, -2, -3\}$ and $L \in \{1, 2, 4, 6, 8, 10\}$.

Criticism to the put-writing strategy

We have to take into account that the HFRI Nordic Hedge Fund Index is an aggregated index consisting of 155 individual Nordic hedge funds. As such, this put-writing strategy cannot say anything about each individual hedge fund's performance in the sample period, but only describes the aggregate performance of the total of the funds. This means that some of the funds contained in the index can still outperform the put-writing strategy.

Data

In order to replicate the put-writing strategy, we have acquired the Nordic Hedge Index Composite (NHX) dataset consisting of monthly observations in the period December 2004 to September 2016 (142 observations). The index consists of hedge funds from five Nordic countries: Norway, Sweden, Denmark, Finland and Iceland. The strategies of the respective hedge funds can be divided into five categories:

Fixed income: hedge fund strategy that earns on pricing differentials in fixed income securities and derivatives.

Equities: long/short positions in mispriced stocks and derivatives with aims to stay market neutral and earn abnormal returns.

Managed futures and CTA: strategy that invests in futures, commodities and foreign currencies through commodity trading advisors (CTAs). Because of the nature of the assets, the funds are considered to provide a great diversification value.

Multi Strategy: uses several investment strategies, and provides great diversification.

Fund of Funds: hedge funds that invest in other hedge funds.

The data sample from December 2004 to September 2005 consists of several smaller and bigger drawdowns, such as the financial crisis in 2008. The various drawdowns allow us to estimate the aggregated risks of the hedge funds, and to match the riskiness with a put-writing strategy.

To measure the volatility we have obtained monthly observations on the CEBOE VIX Index for the same period as the NHX. In order to find the risk free rate applied in the strategy we have obtained the 10-year Treasury bill, monthly observations in the same period as the NHX dataset. Lastly, we will acquire the daily closing price of put options on the S&P 500 Index.

References

Agarwal, V., & Narayan, N. Y. (2004). Risks and portfolio decisions involving hedge funds. *Review of Financial Studies 17*, pp. 63-98.

Agarwal, V., Mullally, K. A., & Naik, N. Y. (2015). Hedge funds: A survey of the academic literature. *Foundations and Trends in Finance*.

Amin, G., & H., K. (2003). Stocks,Bonds and Hedge funds, Not a free lunch! *Journal of Portfolio Management 29*, pp. 113-220.

Asness, C., Krail, R., & Liew, J. (2001). Do hedge funds hedge? *Journal of portfolio Management 28*, pp. 1-19.

Avramov, D., Kosowski, R., Y, N. N., & Teo, M. (2011). Hedge funds, managerial skill, and macroeconomic variables. *Journal of Financial Economics 99*.

Bali, T. G., Brown, J., & Caglayan, M. O. (2011). Systematic risk and the cross-section of hedge funds returns. *Journal of Financial Economics*.

Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy 81*, pp. 617-654.

Bollen, N. P., & Pool, V. K. (2009). Do hedge fund managers misreport returns? Evidence from the pooled distribution. *Journal of Finance 64*, pp. 2257-2288.

Brown, S., & J.F., S. (2006). Caught by the tail:Tail risk neutrality and hedge fund returns. *Stern School of Business*.

Carhart, M. (1997). On persistence in mutual fund performance. *Journal of Finance 52*, pp. 57-82.

Cave, A., Hübner, G., & Sougne, D. (2011). The market timing skills of hedge funds during the financial crisis. *Managerial Finance 30*.

Fama, E. F., & French, K. (1992). The cross-section of expected stock returns. *The Journal Of Finance*.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics 33*, pp. 3-56.

Fama, E. F., & French, K. R. (2010). Luck versus skill in the cross-section of mutual fund returns. *Journal of Finance 65*, pp. 1915-1947.

Fung, W., & Hsieh, D. (2001). The risk in hedge fund Strategies: Theory and evidence from trend followers. *Review of Financial Studies 14*, pp. 313-341.

Fung, W., & Hsieh, D. (2004). Hedge fund benchmark: A risk based approach. *Financial Analysts Journal 60*, pp. 65-80.

Fung, W., & Hsieh, D. A. (1997). Empirical characteristics of dynamic trading strategies: the case of hedge funds. *The Review of Financial Studies 14*.

Getmansky, M. (2004). The life cycle of hedge funds: Fund flows, size and performance. *Sloan School of Management*.

Hasanhodzic, J., & Lo, A. W. (2007). Can hedge fund returns be replicated?: The linear case. *Journal of Investment Management 5*, pp. 5-45.

Ibbotson, R. G., Chen, P., & Zhu, K. X. (2010). The ABCs of hedge funds: Alphas, Betas, and costs, working paper. *Yale School of Management*.

Joenväärä, J., Kosowski, R., & Pekka, T. (2016). Hedge fund performance: What do we know? *Centre for Hedge Fund Research*.

Jurek, J. W., & Stafford, E. (2015). The cost of capital for alternative investments. *The Journal of Finance 5*, pp. 2185-2226.

Lo, A. W. (2001). Risk management for hedge funds: Introduction and overview. *Financial Analysts Journal 6*, pp. 16-33.

Malkiel, B. G., & Saha, A. (2005). Hedge Funds: Risk and return. *Financial Analysts Journal*.

Patton, A. J. (2009). Are "market neutral" hedge funds really market neutral? *Review of Financial Studies 22*, pp. 2495-2530.

Ross, S. (1976). The arbitrage pricing theory approach to strategic portfolio planning. *Financial Analyst Journal*.