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Do hedge funds yield greater risk-adjusted rate of returns than mutual funds?

A QUANTITATIVE STUDY COMPARING HEDGE FUNDS TO MUTUAL FUNDS AND HEDGE FUND STRATEGIES

OSCAR BÖRJESSON, SEBASTIAN HAQ

KTH ROYAL INSTITUTE OF TECHNOLOGY

SCI SCHOOL OF ENGINEERING SCIENCES

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OSCAR BÖRJESSON
SEBASTIAN HAQ

Degree Project in Applied Mathematics and Industrial Economics (15 credits)
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Supervisor at KTH was Camilla Johansson Landén
Examiner was Tatjana Pavlenko

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Royal Institute of Technology
School of Engineering Sciences

KTH SCI
SE-100 44 Stockholm, Sweden

URL: www.kth.se/sci

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Abstract

In recent times, the popularity of hedge funds has undoubtedly increased. There are shared opinions on whether hedge funds generate absolute rates of returns and whether they provide a strong alternative investment to mutual funds. This thesis aims to examine whether hedge funds with different investment strategies create absolute returns and if certain investment strategies outperform others. This thesis compares hedge funds risk-adjusted rate of return towards mutual funds, such as mutual funds, to see if certain investment strategies are more lucrative than the corresponding investments in terms of excess returns to corresponding indices. An econometric approach was applied to search for significant differences in risk-adjusted returns of hedge funds in contrast to mutual funds.

Our results show that Swedish hedge funds do not generate as high risk-adjusted returns as Swedish mutual funds. In regard to the best performing hedge fund strategy, the results are inconclusive. Also, we do not find any evidence that hedge funds violate the effective market hypothesis.

Keywords: hedge fund, absolute returns, hedge fund strategies, regression analysis, mutual funds, risk-adjusted return, Sharpe ratio, Effective market hypothesis

JEL classification: G10; G11; G12; G15; G23

Avkastar hedgefonder högre risk-justerade avkastningar än aktiefonder?

En kvantitativ studie som jämför hedgefonder med aktiefonder och investeringsstrategier

Sammanfattning

Hedgefonder har den senaste tiden ökat i popularitet. Samtidigt finns det delade meningar huruvida hedgefonder genererar absolutavkastning och om de fungerar som bra alternativ till traditionella fonder. Denna uppsats syftar till att undersöka huruvida hedgefonder skapar absolutavkastning samt om det finns investeringsstrategier som presterar bättre än andra. Denna uppsats jämför hedgefonders riskjusterade avkastning med traditionella fonder, för att på sätt se om en viss investeringsstrategi är mer lukrativ i termer av överavkastning i förhållande till motsvarande index. Vi har använt ekonometriska metoder för att söka efter statistiskt signifikanta skillnader mellan avkastningen för hedgefonder och traditionella fonder.

Våra resultat visar att svenska hedgefonder inte genererar högre risk-justerade avkastningar än svenska aktiefonder. Våra resultat visar inga signifikanta skillnader vad gäller avkastning mellan olika strategier. Slutligen finner vi heller inga bevis för att hedgefonder går emot den effektiva marknadshypotesen.

Nyckelord: hedgefond, absolutavkastning, hedgefondsstrategier, regressionsanalys, aktiefond, riskjusterad avkastning, Sharpekvot, Effektiva marknadsteorin

JEL classification: G10; G11; G12; G15; G23

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Stockholm, 26^{th} May, 2014

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1 Introduction

↪ *In this section we give the problem background and introduce the problem formulation, i.e. which questions this thesis aims to answer. We then write about the limitations and methodology.*

1.1 Problem background

Hedge funds often use complex investment strategies to succeed in generating absolute returns[1] and have unconstrained allocation rules in contrast to mutual funds. This results in fund managers having greater possibilities to take speculative positions on the market. The word "hedge" in hedge funds refers to the fact that hedge funds traditionally tend to use hedging techniques. However hedge funds do not have to engage in these types of practices. Hedge funds are often not as regulated as the corresponding mutual funds and they therefore often bypass different types of licensing requirements that are applicable to other types of funds, such as mutual funds. In recent years, increased popularity of hedge funds has made it into one of the main investment products and also one of the largest sources of capital.

1.2 Problem statement

Due to the increased popularity of hedge funds, there are reasons to fully investigate whether hedge funds in fact does reach their goals of generating stable positive returns. In order to conduct such an investigation, this thesis attempts to answer the following questions:

- Does hedge funds yield greater risk-adjusted returns than mutual funds?
- Is there an investment strategy which is used more frequently than others?
- Can Swedish hedge funds' returns be explained by the effective market hypothesis?

1.3 Aim

This report aims to investigate the difference in risk-adjusted return for hedge funds and mutual funds, what hedge fund strategy is the preferred strategy among Swedish hedge fund managers and also if the effective market hypothesis can be used to explain the return of hedge funds. The aim is to provide an insight into the Swedish hedge fund industry. The results could be used to motivate the use of certain hedge fund strategies.

1.4 Limitations

This thesis will concentrate on funds with Sweden as legal domicile. Furthermore, we have chosen to focus on four dominant hedge fund strategies in such way that other strategies might be categorized under our strategies of choice. We have also chosen the time period between 2011 and 2014. This is in order to get results that show how the funds perform during "neutral" market conditions. For hedge funds, an interesting question is of course if they generate stable and positive returns during financially distressed periods. This is however beyond the scope of this thesis, since the question is if hedge funds can outperform mutual funds during ordinary market circumstances.

[1] http://www.investopedia.com/terms/a/absolutereturn.asp

1.5 Methodology

In order to successfully conduct the investigation and analysis, this thesis will use the following three methods:

1.5.1 Literature studies

We have studied scientific literature in order to get a deeper understanding of different hedge fund strategies. Several studies of hedge funds in relation to mutual funds have been made. However, none has been made for Swedish markets. The scientific studies are discussed in detail in Section 2.7.

The papers used in this thesis were found using the KTH library search function for publications. The search words were “hedge funds” and ”hedge fund strategies” with the topics: “hedge funds”, “hedge fund” and “performance” and ”hedge fund strategies” , ”performance” and ”hedge funds”, respectively. The search only included peer-reviewed material and the papers chosen were those considered the most relevant.

1.5.2 Interviews

In order to understand how certain Swedish hedge fund managers allocate capital in different funds, we interviewed three fund managers from two different hedge funds. This also provided another point of view, complementing scientific studies, since theoretical justifications might be different for practical purposes. The selection of interview candidates were made by contacting fund managers through mail, inviting them to meet with us for a interview. The fund managers that responded were interviewed. The interviews were conducted as open conversations with hedge fund strategies as the only guideline.

1.5.3 Statistical calculations

The statistical methods include calculations that examines whether hedge funds outperforms mutual funds with the use of regression analysis. We improve on an initial model by using different criterion. We also use statistical tools that alleviates problems that might occur between models. The calculations will be based on the Morningstar database for Swedish mutual and hedge funds.

2 Theoretical framework

↪ *This section provides the theoretical framework for understanding the specification of the regression model. It consists of theory within the field of corporate finance as well as classification of different hedge fund strategies and finally previous studies.*

2.1 Effective market hypothesis

The efficient market hypothesis states that the price of all securities is fair, based on future cash flow, given all the information that is available to investors. This means that it is not possible to constantly outperform corresponding market indices with the information available to all investors. The information available to all investors is information found in news reports, financial statements, corporate press releases or information from other data sources.[1]

The reasoning behind the efficient market hypothesis is that investors are expected to be very competitive and therefore the market should react instantaneously to new information concerning a security, meaning that the price of said security should converge to the "true" price in a short time period.

Eugene Fama is the originator of the EMH and therefore supports passive management, i.e. management through index. He believes that the stock market reacts on all information at such a fast pace that it is not possible to choose stocks that are better than the average. Robert Schiller, on the other hand, agrees with Fama's theory that the stock market is effective on the short run. However, he shows that there are possibilities for an active manager to beat stock market indices on the long run[2].

2.2 Sharpe ratio

The Sharpe ratio is the ratio between the excess return of an asset and the asset's volatility. The excess return is in this case the return of the asset minus the return of a benchmark asset e.g. an index or the risk-free interest rate. In other words, the Sharpe ratio describes the compensation investors get for taking a risk. The Sharpe ratio can be used to compare different assets with a common benchmark asset, the asset with the highest Sharpe ratio provides either higher return for the same risk or the same return for lower risk. The Sharpe ratio can also be used as an instrument to measure the performance of an investment [1].

$$Sharperatio = \frac{ExcessReturn}{Volatility} = \frac{E(r_a - r_f)}{\sigma_a} \tag{1}$$

According to equation (1) the Sharp ratio is calculated as the difference between the rate of return of the asset and a benchmark asset divided by the standard deviation of the difference, in accordance with the Morningstar definition.

2.3 Jensen's alpha

Jensen's alpha is best described as a risk-adjusted measure of a portfolio's performance, or return on an investment created by active management. Thus, it estimates the contributions to a fund's return that is actively created by a manager, or the managers predictive

[2] http://www.kva.se/Documents/Priser/Ekonomi/2013/pop_en_13.pdf

abilities. This risk-adjusted measure is used to predict the returns that are created in excess of a corresponding passively managed portfolio given a certain risk level. In order to access the relative performance, a benchmark is often subtracted from the performance, in order to achieve Jensen's alpha [2].

It is normally argued that the expected value of alpha is zero, $E(\alpha) = 0$, in an efficient market. According to this setting, alpha can be used to measure the performance of an asset based on the risk it has taken. A manager with strong ability to predict market timing will have a significantly positive α due to consistent positive residuals. In the same manner, a manager that consistely achivies lower performance will have a significantly negative α.[1]

2.4 Benchmark selection

Benchmarks can be best described as an objective standard used for the comparison and evaluation of the performance of an asset. The importance of choosing the correct benchmark for an asset lies in that it must, in an adequate manner, reflect the particular style that an investment manager uses. Since hedge funds does not explictly make use of benchmarks as comparison tools for evaluating performance, we choose the risk-free rate of interest, 10 year Swedish government bond[3]. In order to make a fair comparison between hedge funds and mutual funds, the risk-free rate of return is used as a benchmark for both fund types. Since, the two fund types have different aims, the benchmark selection can be questioned. However, this will be discussed more in detail in the analysis.

2.5 Difference between hedge funds and mutual funds

The table below describes the common features of hedge funds and mutual funds, thus presenting the differences of the fund types. Hedge fund placements rules are normally

Table 1: Difference hedge funds and mutual funds

	Hedge funds	**Mutual Funds**
Placement rules	Free	Limited
Return target	Absolute return	Relative returns
Outlook on risk	Lose money	Deviate from index
Investment philosophy	Limit market risks by combining long and short positions	Market risk by taking long positions
Measure of success	High yield compared to risk	Exceed market index
Fee system	Fixed and performance-based	Fixed
Fund manager investments	Very common	Uncommon

much more free than mutual funds. Hedge funds can take positions in different financial derivatives in order to increase their returns, whereas mutual funds often subjected to strict regulations which allows them only to take long positions and therefore the risk exposure normally is in form of market risk.[3]

[3]http://www.riksbank.se/sv/Rantor-och-valutakurser/

2.6 Hedge fund investment strategies

Hedge funds can best be described as investment vehicles that are speculative in nature and designed to take advantage of information that is held by the hedge fund managers. It is in the hands of the fund manager to decide when the information is no longer useful in terms of making trades, and only then will it not be kept a secret. Hedge fund managers are therefore, quite reasonably, also reluctant to revealing information about investment strategies, since this might turn out to uncover essential information about different positions that hedge funds are likely to take. The major investment strategies can be outlined into four categories based on what type of positions the hedge funds engage in. Independent of the strategy, it is of vast importance that hedge funds have a low correlation with the financial markets. This is essential since hedge funds should remain stable during economic recessions[4]. The descriptions of the four different strategies below are based on *An Introduction to Hedge Funds, Introductory Guide* [4].

2.6.1 Long/short strategies

One of the most common strategies is the long/short strategy. This strategy involves taking long or short positions, where taking short positions refers to hedge fund managers using the strategy of selling securities that are not currently possessed by the fund. This allows them, unlike mutual funds, to speculate in the price falls. Strategies involving taking long and short positions separate market risk from the risk of the individual stock.

2.6.2 Relative value strategies

The relative value strategies are used to exploit arbitrage opportunities. These strategies trust that mispriced securities will return to their intrinsic value in the long run, however with deviations in the short run that will open up opportunities for profit. There are several ways of exploiting arbitrage opportunities, and amongst them are: convertible arbitrage, capital arbitrage, fixed income arbitrage, yield curve arbitrage and corporate spread arbitrage. The underlying principle is that the market has in some way mispriced an asset or asset class, relative to other assets, and with the assumption that in the long run the market will move back to equilibrium levels, short-term profits can be made.

2.6.3 Event-driven strategies

Event-driven strategies are highly speculative in nature. They rely on an approach that is based on events that will influence the market during a short period of time. Examples of an event that affects the market might be stock buybacks or earnings surprises. This hedge fund strategy also relies on that hedge fund managers are in possession of superior information that can be exploited in order to make stronger returns. An event driven strategy that is commonly used amongst hedge funds are distressed securities investing, which implies that hedge funds takes long positions in securities that are currently experiencing financial problems, such as firms that have filed for credit protection or are priced over their intrinsic value in contrast to counterparts in the same industry.

2.6.4 Global macro strategies

In tactical strategies of trading, the main objective is to forecast the direction of the market movements and thus forecasting the profits of the securities of a certain industry.

[4] http://www.brummer.se/sv/Om-oss/Vad-ar-hedgefond/

In this type of strategy, the timing of entering certain positions as well as how well the fund manager can predict the price movements in an industry is of great importance. One often-used strategy is the pure macro strategy that involves taking advantage of macroeconomic events such as a change in stock market performance, interest rates or market trends. Hedge funds that engage in macro strategies extensively use financial derivatives as well as leverage in order to forecast major economic trends and then invest in asset classes or certain countries where an investment opportunity can be found.

2.7 Previous studies

2.7.1 Hedge funds vs mutual funds

Due to hedge funds growing popularity, they have been under quite hefty scrutiny. Many investors consider hedge funds an alternative investment to traditional stocks and bonds. Thus, in recent times, the number of articles that discuss whether hedge funds have a higher risk-adjusted performance than mutual funds has increased drastically.

Ackerman, McEnally, Ravenscraft (1999) compare hedge funds to mutual funds in terms of risk-adjusted performance and Sharpe ratio in their paper *The Performance of Hedge funds: Risk, Return, and Incentives.* They find that hedge funds consistently outperform mutual funds. They also compare hedge funds to standard market indices and they conclude that market indices are not outperformed. Amongst the conclusions are also that hedge funds are more volatile than both market indices and corresponding mutual funds. Incentive fees can, to some extent, explain hedge fund performance. However the incentive fees cannot explain the total risk taken by the portfolio [5].

Liang (1998) examines in the paper *On the Performance of Hedge Funds* the performance and risk of hedge funds during the period 1994-1996, and concludes that hedge funds show a rather low correlation with financial markets and to other hedge funds. This is exemplary good for the diversification of a portfolio. Liang finally concludes that hedge funds are better investment vehicle than mutual funds. This is because Liang showed that hedge funds have a higher Sharpe ratio than mutual funds, and they generally show a higher performance rate relative to the remaining financial markets during the period of examination [6].

Dichev and Yu (2011) compares the investor returns of hedge funds and buy-and-hold fund returns in their paper *Higher risk, lower returns: What hedge fund investors really earn.* Their main finding is that annualized dollar-weighed returns are 3-7% lower than the corresponding buy-and-hold funds. Also, using a factor model of risk and the estimated dollar-weighted performance gap they come to the conclusion that the real alpha of hedge fund investors is close to zero [7].

Capocci and Hübner (2004) investigate the performance of different hedge fund strategies using asset pricing models in their paper *Analysis of hedge fund performance.* Using CAPM, Fama-French and Agarwal's and Naik's asset pricing models with the addition of a factor taking into account that some hedge funds invest in emerging market bonds, they come to the conclusion that one fourth of all hedge funds deliver significant positive excess returns and 10 of 13 strategies offer significantly positive return. They also find that the best performing funds use momentum strategies, they do not invest in emerging markets and they prefer low-book-to-market stocks [8].

2.7.2 Hedge fund investment strategies

Brown, Goetzmann and Ibottson (1999) examine in their paper *Offshore Hedge Funds: Survival and Performance* how successful offshore hedge funds have been in terms of Jensen's alpha. They categorize 10 different types of funds, and show that all the categories show a positive alpha except short selling. In all cases, the alpha was statistically significant. Since the examined hedge funds had a low correlation with the U.S. stock and bond market, the authors conclude that the hedge funds can be used for portfolio diversification [9].

Olmo and Sanso-Navarro (2012) predict the relative performance of hedge fund investment strategies in their paper *Forecasting the performance of hedge fund styles* By using time-varying conditional stochastic dominance tests they forecast the return of hedge funds. More specifically they forecast the return of hedge funds during the recent financial crisis and come to the conclusion that global macro strategy outperform the other strategies. They also observe that different factors have more or less influence over the predictions depending on the region of the returns distribution and that the Fung and Hsieh factors (asset-based style factors) can be used for hedge fund return density forecasting [10].

Fung and Hsieh (2011) investigates the long/short strategy hedge funds in their paper *The risk in hedge fund strategies: Theory and evidence from long/short equity hedge funds*. They find that less than 20% of the 3000 viewed long/short hedge funds were able to deliver persistent and significant positive alpha. They also find that evidence point to alpha decaying over time. However, they don't find evidence that support that size has a negative effect on alpha. They also make a comment stating that, even though long/short strategies have a small representation of alpha performing funds, they still outperform equity mutual funds [11].

3 Mathematical theory

↪ *In this section, we introduce the statistical theory used for conducting the regression analysis. We also provide the theory for the methods used for optimizing our regression models.*

3.1 Linear regression model

The multiple linear regression model is specified according to:

$$y_i = \sum_{j=0}^{k} x_{ij}\beta_j + e_i, i = 1, ..., n \tag{2}$$

where y_i is the dependent random regressand for each observation, wheras the x_{ij} are covariates. The regression coefficients are denoted β_j and the error terms are denoted e_i, which are assumed to be independent between observations. The multiple linear regression model can compactly be written as:[12]

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{e} \tag{3}$$

where,

$$\mathbf{Y} = \begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix} \boldsymbol{\beta} = \begin{pmatrix} \beta_0 \\ \vdots \\ \beta_k \end{pmatrix} \mathbf{e} = \begin{pmatrix} e_0 \\ \vdots \\ e_n \end{pmatrix}$$

$$\mathbf{X} = \begin{pmatrix} x_{1,0} & x_{1,1} & \cdots & x_{1,k} \\ x_{2,0} & x_{2,1} & \cdots & x_{2,k} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n,0} & x_{n,1} & \cdots & x_{n,k} \end{pmatrix}$$

3.1.1 Key assumptions:

These assumptions can be found more in detail in *Introduction to econometrics* [13].

1. The conditional distribution of e_i given $x_{1j}, ..., x_{nj}$ has a mean of zero.
2. $x_{1j}, ..., x_{nj}$ for $i = 1, 2, ..., .n$ are i.i.d.
3. Large outliers are unlikely.
4. There is no perfect multicollinearity.

3.1.2 R^2 and Adjusted-R^2

R^2 and Adjusted-R^2 are both used as measures of goodness of fit. According to the setting below $\hat{y}$ is the predicted value of y and $\bar{y}$ is the mean value of y.

$$R^2 = 1 - \frac{\sum_{i=0}^{N} (y_i - \hat{y}_i)}{\sum_{i=0}^{N} (y_i - \bar{y}_i)} \tag{4}$$

The adjusted-R^2 is a modified version of R^2 that takes into account the addition of a new variable. It can therefore either decrease or increase when adding a new variable, depending if the variable helps explain Y or not.

$$R^2 = 1 - \frac{n-1}{n-k-1} \frac{\sum_{i=0}^{N} (y_i - \hat{y}_i)}{\sum_{i=0}^{N} (y_i - \bar{y}_i)} \tag{5}$$

Equation (5) shows that the adjusted-R^2 is 1 minus the ratio of the sample variance of the OLS residuals (with degree of freedom correction) to the sample variance of Y.[13]

3.1.3 F-statistic & t-test

The t-test is used to test the null hypothesis that an estimated covariate of the regression model is equal to a constant. The t-statistic can be used when testing the null hypothesis, $H_0 : \beta_i = 0$. Under the null hypothesis t belongs to student's t distribution with $n-k-1$ degrees of freedom, with n being number of observations and k being number of covariates in the regression model. The t-statistic is given by:

$$t = \frac{\hat{\beta}_i - \beta_i}{SE(\hat{\beta}_i)} \tag{6}$$

where $\hat{\beta}_i$ is the estimated covariate, β_i is the constant and $SE(\hat{\beta}_i)$ is the standard error of the estimated covariate i. The p-value for the null hypothesis is:

$$p = 2\Pr(T \geq |t|) \tag{7}$$

where $T \in t(n-k-1)$.

When testing the null hypothesis that several covariates are zero, the F-test is used. The F-statistic is given by:

$$F = \frac{n-k-1}{r} \left(\frac{|\hat{e_*}|^2}{|\hat{e}|^2} - 1 \right) \tag{8}$$

where $|\hat{e}|^2$ is the sum of squared residuals for the full model and $|\hat{e_*}|^2$ is the sum of squared residuals for the model with the tested covariates set to zero, n and k is the same as for the t-test and r is the number of tested covariates. The p-value of the null hypothesis is:

$$p = \Pr(X > F) \tag{9}$$

where $X \in F(r, n-k-1)$. [12]

3.2 Probit model & maximum likelihood

For the probit model, the dependent variable $Y_i, i = 1, ..., n$, is defined as a binary variable. The probability that $Y_i = 1$, conditional on $x_{i1}, ..., x_{ik}$, is calculated as $p_i = \phi(\beta_0 + \beta_1 x_{i1} + \cdots + \beta_k x_{ik})$. The conditional probability distribution for the i^{th} observation is $\Pr(Y_i|x_{i1}, ..., x_{ik}) = p_i^{y_i}(1-p_i)^{1-y_i}$. Assuming that $(x_{i1}, ..., x_{ik}, Y_i)$ are i.i.d., $i = 1, ..., n$, the joint probability distribution of $Y_1, ..., Y_n$ conditional on the covariates is

$$\begin{aligned}
&\Pr(Y_1 = y_1, ..., Y_n = y_n | x_{i0}, ..., x_{ik}, i = 1, ..., n) \\
&= \Pr(Y_1 = y_1 | x_{10}, ..., x_{1k} \times \cdots \times \Pr(Y_n = y_n | x_{n0}, ..., x_{nk}) \\
&= p_1^{y_1}(1-p_1)^{1-y_1} \times \cdots \times p_n^{y_n}(1-p_n)^{1-y_n}
\end{aligned} \tag{10}$$

The likelihood function is the joint probability distribution, treated as a function of the unknown coefficient. It is conventional to consider the logarithm of the likelihood. Accordingly, the log-likelihood function is:

$$\begin{aligned}
&ln[f_{probit}(\beta_0, ..., \beta_k; Y_1, ..., Y_n | x_{0i}, ..., x_{ki}, i = 1, ..., n)] \\
&= \sum_{i=1}^{n} Y_i ln[\phi(\beta_0 + \beta_1 x_{1i} + \cdots + \beta_k x_{ki})] \\
&+ \sum_{i=1}^{n} (1 - y_i) ln[1 - \phi(\beta_0 + \beta_1 x_{1i} + \cdots + \beta_k x_{ki})]
\end{aligned} \tag{11}$$

where this expression incorporates the probit formula for the conditional probabiliy, $p_i = \phi(\beta_0 + \beta_1 x_{1i} + \cdots + \beta_k x_{ki})$. The MLE for the probit model maximizes the likelihood function, or equivalently, the logarithm of the likelihood function given in equation above. Because there is no simple formula for the MLE, the probit likelihood function must be maximized using a numerical algorithm. Under general conditions, maximum likelihood estimators are consistent and have a normal sampling distribution in large samples.[13]

3.2.1 Pseudo-R^2

In probit regression, pseudo R-squared are used, since probit regression does not have en equivalent to the usual R-squared used in OLS regression. Therefore McFadden's pseudo R-squared is normally used:

$$R^2 = 1 - \frac{ln(\hat{L}(M_f))}{ln(\hat{L}(M_i))} \tag{12}$$

According to this setting, M_f is the model with predictors, and M_i is the model without predictors, and $\hat{L}$ is the estimated likelihood. The log-likelihood of the intercept model is treated as a total sum of squares and the log-likelihood of the full model is treated as the sum of squared errors.[13]

3.3 Stepwise regression & backward elimination method

In order to find a regression model that is optimized for solving our thesis question, we use a stepwise regression method. Specifically will we use the backward elimination method. This method uses the particular procedure:

1. All covariates are included in our intial multiple linear regression model.
2. We test the deletion of each covariate from regression using the criterions.
3. We delete the covariates that improves the model most without losing explanatory power, and then repeat this process until we cannot further improve our model.

We will use the stepwise regression method by two different criterions, namely the Bayesian Information Criterion and teh Akaike Information Criterion.

3.3.1 Bayesian Information Criterion (BIC)

Regression models can be overfitted by having too many covariates. A common test for this is the BIC (Bayesian Information Criterion) test. One chooses the model that minimizes:

$$nln(|\hat{e}^2|) + kln(n) \tag{13}$$

where k is the number of covariates (including the intercept) and n the number of observations and $|\hat{e}^2|$ is the sum of squares.[12]

3.3.2 Akaike Information Criterion (AIC)

In addition to BIC, there is another way of determining if a covariate should enter the equation, AIC (Akaike Information Criterion). AIC differs from BIC in the second term, where instead of "$ln(n)$" there is "2". So the preferred model is the one that minimizes:

$$nln(|\hat{e}^2|) + 2k \tag{14}$$

where k is the number of covariates (including the intercept), n the number of observations and $|\hat{e}^2|$ is the sum of squares.[13]

3.4 Heteroskedasticity

Heteroskedasticity is when the variance of the error terms differ between observations. For instance, an example of heterskedasticity is when the variance of the error terms depend on the values of the covariates. Heteroskedasticity can be detected by plotting the residuals against every covariate. If there is a correlation, then there are signs of heteroskedasticity.[12]

3.5 Correction for heteroskedasticity

When computing the regressions in our statistical software, we use a setting allowing us to correct for heteroskadasticity. We get heteroscedascity robust standard errors accordingly. This is equivalent to White's consistent variance estimator, which is defined accordingly:

$$\begin{aligned} Cov(\hat{\beta}) &= (\mathbf{X}^t\mathbf{X})^{-1}\mathbf{X}^t D(\hat{e}^2)\mathbf{X}(\mathbf{X}^t\mathbf{X})^{-1} \\ &= (\mathbf{X}^t\mathbf{X})^{-1}\left(\sum_{-1}^{n}\hat{e}_i^2 x_i^t x_i\right)(\mathbf{X}^t\mathbf{X})^{-1} \end{aligned} \tag{15}$$

where $D(\hat{e}^2)$ is the $n \times n$ diagonal matrix whose ith diagonal element is $\hat{e}_i^2$.[12]

3.6 Multicollinearity

When two or more of the covariates in a regression model are linearly or close to linearly dependent it is called multicollinearity. Perfect multicollinearity, where some covariates are perfectly correlated is rare. When multicollinearity occur, at least one of the covariates must be removed. For example, in a situation where we have several dummy variables that are mutually exclusive, there is perfect multicollinearity. By removing one of these covariates and making it the benchmark, the multicollinearity is fixed. A sign of multicollinearity is large standard deviations for the affected covariates. [12] Another sign is a high variance influence factor (VIF). If $VIF < 10$ it is considered a problem for the estimation of the covariates. R_i^2 is calculated by having the covariate i as the dependent variable against the other covariates in the model. A high R_i^2 indicates that covariate i is explained well by the other covariates.[14]

$$VIF_i = \frac{1}{1 - R_i^2} \tag{16}$$

3.7 Endogeneity

When at least one covariate is related to the error term, the model suffers from endogeneity. This violates key assumption 1 of the linear regression model found in section 3.1.1. Endogeneity can occur when there are omitted variable bias or simultaneous causality bias.[12]

3.8 Shapiro-Wilk test

The Shapiro-Wilk test, calculates a W-statistic that tests whether a random sample, $x_1, x_2, ..., x_n$ comes from a normal distribution. Small values of W are evidence of departure from normality.[5]

$$W = \frac{\left(\sum_{i=1}^{n} a_i x_{(i)}\right)^2}{\sum_{j=1}^{n}(x_i - \bar{x})^2} \tag{17}$$

[5] NIST/SEMATECH e-Handbook of Statistical Methods

4 Data management

↪ *In this section we discuss the different data that is used and provide descriptive statistics for the dataset used for the regressions. We also discuss the different biases that occur in the dataset, and how they can be countered.*

4.1 Collection of data

The data was collected from the Morningstar database, with own modifications such that relevant statistical test could be performed.

4.2 Sample selection

The data used in the regression is composed of 79 Swedish hedge funds and 405 Swedish mutual funds for a total of 484 funds, found at the Swedish Morningstar website. Since there, in Sweden, are quite few hedge funds, the total amount of data is very limited. This limitation affects the possibility to make restrictions when selecting data and therefore, in order to have a sufficient amount of data, the hedge fund data for this report was selected with the sole restriction that they have to be Swedish. Because of limited data for each fund the amount of hedge funds was reduced to 62 and the amount of mutual funds was reduced to 291 for a total of 353 funds.

4.3 Descriptive statistics

The table below shows the mean, standard deviation and the minimum and maximum values of the funds.

Table 2: Descriptive statistics

covariate	Mean	Std.dev	Min	Max
Sharpe	1.96299	1.945002	-2.823596	11.33571
Beta	1.215866	1.214264	-2.898788	4.428485
HedgeFund	0.1756374	0.3810515	0	1
NAV	4076.039	58496.72	3	1090380
KIID	5.467422	0.9562524	2	7
KIID1	0	0	0	0
KIID2	0.0141643	0.1183357	0	1
KIID3	0.0.0538244	0.2259911	0	1
KIID4	0.0594901	0.2368754	0	1
KIID5	0.0.2209632	0.4154846	0	1
KIID6	0.6260623	0.4845342	0	1
KIID7	0.0254958	0.157849	0	1
Domestic	0.9773371	0.1490376	0	1
Foreign	0.509915	0.5006113	0	1
FixedFee	1.348244	0.6545351	0	3.24
PerformanceFee	4.631728	8.197166	0	25
Leverage	0.1444759	0.3520707	0	1
Age	13.26253	8.575832	0.1479452	56.32055
LongShort	0.0679887	0.2520838	0	1
EventDriven	0.0084986	0.0919255	0	1
GlobalMacro	0.0339943	0.1814718	0	1
RelativeValue	0.0084986	0.0919255	0	1
Dividends	0.1444759	0.3520707	0	1
OpenToPublic	0.0.9490085	0.2202926	0	1

4.4 Variable specification

KIID
KIID (Key Investor Information Documents) refers to the risk listed in the fund information folders. It consists of a scale from one to seven, were every level translates to an interval of volatility, with level one being the lowest level of risk and level seven being the highest.

Domestic
A dummy for funds allocating parts of capital in Sweden. This covariate does not exclude foreign allocations.

Foreign
A dummy for funds allocating parts of capital outside Sweden. This covariate does not exclude domestic allocations.

FixedFee
The fee the fund charges in order to run the fund. The investor is required to pay this fee regardless of the fund's performance. This fee is part of the model because a higher fee should mean a better performance since no one would pay a high fee for a bad product.

PerformanceFee
The extra fee the fund charges if it outperforms its benchmark. It is listed in the data as percent of result. This fee is part of the model because a performance fee should function as an incentive for managers, therefore a higher performance fee should give greater return. Also without the greater performance no one would invest in a fund with more fees.

Leverage
A dummy variable describing whether the fund is allowed to use borrowed funds or not. Leverage is part of the model since it can enhance the returns of a fund if used wisely.

Age
The age of the fund, listed in years.

HedgeFund
A dummy variable which makes it possible to distinguish between mutual funds and hedge funds.

LongShort
A dummy variable describing if the hedge fund is using a long/short strategy or not.

Eventdriven
A dummy variable describing if the hedge fund is using an event driven strategy or not.

GlobalMacro
A dummy variable describing if the hedge fund is using a global macro strategy or not.

RelativeValue
A dummy variable describing if the hedge fund is using a relative value strategy or not.

Dividend
Dummy variable describing if the fund pays dividends or not. Dividends could help describe the return of a fund because a dividend paying fund use less of its earnings to invest in assets and should therefore have a smaller return.

OpenToPublic
A dummy variable describing if the fund is open to the public or not. This could help describe the return of a fund because of the difference in management and customer base.

NAV
Net Asset Value for the fund, collected 2014-03-15.

MarketCorr
A variable describing the market correlation of the funds.

StdDev3y
The funds standard deviation for the period 2011-03-15 to 2014-03-15. The variable measures how much the funds performance has deviated in average during the last 36 months from the average return.

4.5 Potential biases

When collecting data in the fashion stated above there are several sources of potential biases. The most general of these, concerns the Morningstar data collection. It is hard to validate that the data collected at Morningstar is legitimate. But since Morningstar is a company with branches in several countries and with a mission to help investors reach their financial goals, any potential bias from them is unlikely since it would contradict their mission and the image of the company.

4.5.1 Survivorship biases

Survivorship bias is known to cause overstatement of performance because funds that cease to trade are not included in the analysis, and these funds often have performed poorly. This creates two problems in the case of hedge funds; fund survivorship and style survivorship. Fund survivorship means overstatement of the true performance of hedge funds. Style survivorship refers to the problem that the styles of surviving funds are different from the styles of deceased funds.

4.5.2 Self selection bias

Contrary to mutual funds, hedge funds are not under the same regulations and therefore can choose the start date of historical performance data. The only incentive for hedge funds to report their performance, is to market their hedge funds. Obviously, hedge fund managers, have an incentive not to report data that impairs the image of the hedge fund. The result of self selection bias is then that the performance data shows better results than the actual performance.

4.5.3 Back-filing bias

Another quite common source of bias is the back-filing bias, that essentially is created when a new hedge fund is added to a database and is asked to provide, for instance, historical data for previous years. In cases when the hedge fund has rather average yields, the hedge fund managers might refuse to supply the complete performance history. Instead, there is a rather strong incentive to hand over a shorter historical data of the performance. The result is that the hedge fund shows a stronger performance than it actually has. In addition, the risk listed in the KIID is only representative for the last five years. This means that for example the financial crisis of 2008 will not be included in the presented risk.

5 Regression models

↪ *In this section, the regression model is discussed as well as methods for evaluating the fit to data. We also show how the variability in the data is taken care of. By improving our intial model, we will move towards a probit model that will allow us to calculate the probability of a higher risk-adjusted rate of return given different hedge fund strategies.*

5.1 Model 1 - Multiple linear regression model

In our first model, we employ a multiple linear regression model which includes all covariates in our dataset. By applying the theory of AIC/BIC we aim to improve the initial model, through the use of stepwise regression, more specifically, backward elimination.

$$\begin{aligned} Sharpe_i = \; & \beta_0 \\ & + \beta_1 HedgeFund \\ & + \beta_2 StdDev3y \\ & + \beta_3 KIID \\ & + \beta_4 Domestic \\ & + \beta_5 Foreign \\ & + \beta_6 Age \\ & + \beta_7 FixedFee \\ & + \beta_8 PerformanceFee \\ & + \beta_9 Leverage \\ & + \beta_{10} LongShort_i \\ & + \beta_{11} EventDriven_i \\ & + \beta_{12} GlobalMacro_i \\ & + \beta_{13} RelativeValue_i \\ & + \beta_{14} Dividends \\ & + \beta_{15} OpenToPublic \\ & + \beta_{16} NAV \\ & + \beta_{17} MarketCorr \\ & + e_i \end{aligned} \tag{18}$$

In Table 4 we see that *HedgeFund* has a VIF above the threshold of ten and the strategy covariates are slightly below ten. This indicates that there is multicollinearity between *HedgeFund* and the strategy covariates. Since these covariates are essential to our analysis this must be resolved. We do this by dividing the model into two separate models, one with the *HedgeFund* covariate as well as all the other covariates exluding the strategy covariates and vice versa.

Table 3: Model 1 fit

Model	**Obs**	R^2	**Adjusted-**R^2	$\mathbf{F}_{(17,335)}$	*Prob.* $> F$
Model 1	353	0.7714	0.7598	48.39	0.000

Table 4: VIF results for Model 1

covariate	**VIF**	**1/VIF**
HedgeFund	18.27	0.054747
EventDriven	7.68	0.130284
RelativeValue	7.43	0.134512
LongShort	6.57	0.152197
Leverage	5.80	0.172492
GlobalMacro	5.48	0.182538
KIID	5.20	0.192282
StdDev3y	3.30	0.303482
PerformanceFee	2.35	0.425910
MarketCorr	1.46	0.685838
Dividends	1.33	0.753924
Fixedfee	1.24	0.808438
Foreign	1.22	0.820296
Age	1.20	0.831204
OpenToPublic	1.19	0.843744
Domestic	1.17	0.853251
NAV	1.17	0.858089
Mean VIF	1.96	

In table 5 we see the correlation between $HedgeFund$ and the strategy covariates. This is further proof of the mentioned multicollinearity.

Table 5: Correlation matrix - Key independent variables

-	HedgeFund
LongShort	0.8491
EventDriven	0.6109
GlobalMacro	0.7187
RelativeValue	0.6109

In table 6 we see that we can reject the hypothesis that the residual is normally distributed at a 5% significance level. This is also verified by both graphs in Figure 1 (see appendix), where the residuals show a steeper curve than that of the normal distribution. In order to remedy this we use White's consistent variance estimator.

Table 6: Shapiro-Wilk test Model 1

Variable	**Obs**	**W**	**V**	**z**	$Prob. > z$
Res	353	0.75063	61.395	9.740	0.00000

5.2 Model 2 - Improved Multiple Regression model

5.2.1 Model 2a

As previously mentioned we do two sets of regression models. In this model the strategy covariates are excluded.

$$
\begin{aligned}
Sharpe_i = \;& \beta_0 \\
& + \beta_1 HedgeFund \\
& + \beta_2 StdDev3y \\
& + \beta_3 KIID \\
& + \beta_4 Domestic \\
& + \beta_5 Foreign \\
& + \beta_6 Age \\
& + \beta_7 FixedFee \\
& + \beta_8 PerformanceFee \\
& + \beta_9 Leverage \\
& + \beta_{10} Dividends \\
& + \beta_{11} OpenToPublic \\
& + \beta_{12} NAV \\
& + \beta_{13} MarketCorr \\
& + e_i
\end{aligned}
\tag{19}
$$

In table 7 we see that both R^2 and adjusted-R^2 has decreased slightly, this was to be expected since the model has fewer explaining covariates. In table 8 we see that VIF is below the threshold of ten, for all covariates. This indicates that there is no multi-collinearity.

In table 9 we see that removing *Dividends*, *Age*, *OpenToPublic*, *Domestic*, *Foreign*, $PerformanceFee$ and *Leverage* from the model will improve BIC and in most cases AIC as well. Since low AIC and BIC indicate a better model these covariates are removed for model 3a.

Table 7: Model 2a fit

Model	**Obs**	R^2	**Adjusted**R^2	**F** $_{(13,339)}$	$Prob. > F$
Model 2b	353	0.7611	0.7519	53.75	0.000

Table 8: VIF results for Model 2a

Covariate	**VIF**	**1/VIF**
HedgeFund	8.91	0.112210
Leverage	5.22	0.191637
KIID	5.20	0.192481
StdDev3y	3.25	0.307722
PerformanceFee	2.25	0.444880
MarketCorr	1.43	0.697816
Dividends	1.27	0.789462
FixedFee	1.22	0.819618
Age	1.20	0.836515
OpenToPublic	1.18	0.848763
Foreign	1.17	0.855284
Domestic	1.10	0.906189
NAV	1.09	0.920129
Mean VIF	2.65	

Table 9: AIC/BIC for Model 2a

Covariate	**ΔAIC**	**ΔBIC**
Dividends	-1,98	-5,84
Age	-1,94	-5,81
OpenToPublic	-1,89	-5,76
Domestic	-1,88	-5,74
Foreign	-1,45	-5,32
PerformanceFee	-1,28	-5,14
NAV	-0,97	-4,84
Leverage	0,90	-2,97
FixedFee	6,20	2,34
HedgeFund	9,82	5,95
StdDev3y	13,28	9,41
KIID	45,35	41,49
MarketCorr	303,58	299,72

In table 10 we see that we can reject that the residuals are normally distributed at a 5% significance level. This is verified by both graphs in Figure 2 (see appendix).

Table 10: Shapiro-Wilk test Model 2a

Covariate	**Obs**	**W**	**V**	**z**	*Prob.* $> z$
Res	353	0.74353	63.144	9.806	0.00000

5.2.2 Model 2b

In this model the covariate $HedgeFund$ is excluded and since we only want to find difference in performance caused by strategies, we exclude the mutual fund data. This leave us with 62 observations.

$$
\begin{aligned}
Sharpe_i = \quad & \beta_0 \\
& + \beta_1 StdDev3y \\
& + \beta_2 KIID \\
& + \beta_3 Domestic \\
& + \beta_4 Foreign \\
& + \beta_5 Age \\
& + \beta_6 FixedFee \\
& + \beta_7 PerformanceFee \\
& + \beta_8 Leverage \\
& + \beta_9 LongShort_i \\
& + \beta_{10} EventDriven_i \\
& + \beta_{11} GlobalMacro_i \\
& + \beta_{12} RelativeValue_i \\
& + \beta_{13} Dividends \\
& + \beta_{14} OpenToPublic \\
& + \beta_{15} NAV \\
& + \beta_{16} MarketCorr \\
& + e_i
\end{aligned}
\tag{20}
$$

In table 11 we see that both R^2 and adjusted-R^2 has decreased, which was expected since covariates were removed. In table 12 we see that VIF is well below the threshold for all covariates and there is no sign of multicollinearity.

In table 13 we see that removing $Leverage$, $Dividends$, $Foreign$, $OpenToPublic$, NAV, $Domestic$, Age and all the strategy covariates will improve BIC and in most cases AIC as well. We therefore remove all these with the exception of the strategy covariates, we leave these in the model since they are key variables.

Table 11: Model 2b fit

Model	**Obs**	R^2	**Adjusted**R^2	**F** $_{(16,45)}$	$Prob. > F$
Model 2b	62	0.7387	0.6457	7.11	0.000

Table 12: VIF results for Model 2b

Covariate	VIF	1/VIF
EventDriven	6.28	0.159216
RelativeValue	5.62	0.177943
StdDev3y	4.57	0.218711
KIID	4.21	0.237788
GlobalMacro	3.54	0.282307
LongShort	2.46	0.407182
Foreign	1.72	0.581325
Age	1.54	0.650638
Domestic	1.51	0.662738
FixedFee	1.43	0.697607
Leverage	1.43	0.697922
MarketCorr	1.39	0.721889
Dividends	1.37	0.730052
NAV	1.35	0.738871
OpenToPublic	1.34	0.744002
PerformanceFee	1.33	0.752973
Mean VIF	2.57	

Table 13: AIC/BIC for Model 2b

Covariate	ΔAIC	ΔBIC
GlobalMacro	-1,9821	-4,1092
Leverage	-1,9681	-4,0952
Dividends	-1,9644	-4,0916
Foreign	-1,5466	-3,6738
OpenToPublic	-1,4682	-3,5953
LongShort	-1,1819	-3,309
RelativeValue	-1,1543	-3,2804
EventDriven	-1,1287	-3,2559
NAV	-0,6732	-2,8004
Domestic	1,3343	-0,7928
Age	1,4158	-0,7113
PerformanceFee	2,1391	0,0119
KIID	2,6132	0,4861
FixedFee	4,8106	2,6835
StdDev3y	8,7417	6,6145
MarketCorr	34,8527	32,7255

In table 14 we see that we cannot reject that the residual is normally distributed at a 5 % significance level. In figure 3 (see appendix) we see that the graphs do not have the same steep curve as the residual graphs from model 1. However it cannot be said that they show a perfect normal distribution.

Table 14: Shapiro-Wilk test model 2b

Covariate	Obs	W	V	z	$Prob. > z$
Res	62	0.96759	1.809	1.280	0.10034

5.3 Model 3 - Final models

Since $KIID$ is divided in uneven intervals, (KIID7 represent 25% or more) we transform $KIID$ into 7 dummy variables, each representing different KIID-levels. Since we use different data for the different sets of regression models and we want to avoid multicollinearity, we use different benchmarks for the different models. If two covariates show high correlation in comparison to the others, one of them will be chosen as benchmark.

5.3.1 Model 3a

In table 15 we see that there is a high correlation between $KIID5$ and $KIID6$ and we therefore choose $KIID6$ as benchmark.

Table 15: KIID Correlation matrix 3a

-	KIID2	KIID3	KIID4	KIID5	KIID6	KIID7
KIID2	1.0000					
KIID3	-0.0286	1.0000				
KIID4	-0.0301	-0.0600	1.0000			
KIID5	-0.0638	-0.1270	-0.1339	1.0000		
KIID6	-0.1551	-0.3086	-0.3254	-0.6891	1.0000	
KIID7	-0.0194	-0.0386	-0.0407	-0.0861	-0.2093	1.0000

$$\begin{aligned} Sharpe_i = \ & \beta_0 \\ & + \beta_1 HedgeFund \\ & + \beta_2 StdDev3y \\ & + \beta_3 KIID2 \\ & + \beta_4 KIID3 \\ & + \beta_5 KIID4 \\ & + \beta_6 KIID5 \\ & + \beta_7 KIID7 \\ & + \beta_8 FixedFee \\ & + \beta_9 MarketCorr \\ & + e_i \end{aligned} \tag{21}$$

In table 16 we see that R^2 and adjusted-R^2 is significantly higher than in the previous models, even though we have removed several covariates. In table 17 we see that VIF is well below the threshold for all covariates and there is no multicollinearity.

Table 16: Model 3a fit

Model	**Obs**	R^2	**Adjusted**R^2	**F** $_{(9,343)}$	$Prob. > F$
Model 3a	353	0.8421	0.8380	122.90	0.000

Table 17: VIF results for Model 3a

Covariate	**VIF**	**1/VIF**
KIID3	3.46	0.288833
HedgeFund	3.46	0.289012
StdDev3y	3.30	0.303277
KIID4	3.17	0.315628
KIID5	1.91	0.524843
KIID2	1.70	0.586574
MarketCorr	1.41	0.708054
FixedFee	1.27	0.786418
KIID7	1.13	0.886676
Mean VIF	2.31	

In table 18 we see that we can reject the hypothesis that the residual is normally distributed. In figure 4 (see appendix) we see that the steepness of the curve has increased and is further from normal than the previous model.

Table 18: Shapiro-Wilk test Model 3a

Covariate	**Obs**	**W**	**V**	**z**	$Prob. > z$
Res	353	0.75031	61.475	9.743	0.00000

5.3.2 Model 3b

In table 19 we see that $KIID3$ and $KIID4$ has the highest correlation and we therefore choose $KIID3$ as benchmark.

Table 19: Correlation matrix - KIID

-	KIID2	KIID3	KIID4	KIID5	KIID6
KIID2	1.0000				
KIID3	-0.1969	1.0000			
KIID4	-0.2044	-0.4587	1.0000		
KIID5	-0.1747	-0.3920	-0.4070	1.0000	
KIID6	-0.0541	-0.1214	-0.1260	-0.1077	1.0000

$$
\begin{aligned}
Sharpe_i = \quad & \beta_0 \\
& + \beta_1 StdDev3y \\
& + \beta_2 KIID2 \\
& + \beta_3 KIID4 \\
& + \beta_4 KIID5 \\
& + \beta_5 KIID6 \\
& + \beta_6 FixedFee \\
& + \beta_7 PerformanceFee \\
& + \beta_8 LongShort_i \\
& + \beta_9 EventDriven_i \\
& + \beta_{10} GlobalMacro_i \\
& + \beta_{11} RelativeValue_i \\
& + \beta_{12} MarketCorr \\
& + e_i
\end{aligned} \tag{22}
$$

In table 20 we see that both R^2 and adjusted-R^2 is higher than in the previous model. In table 21 we see that VIF is below the threshold for all covariates and there is no multicollinearity.

Table 20: Model 3b fit

Model	**Obs**	R^2	**Adjusted**R^2	**F** $_{(11,341)}$	$Prob. > F$
Model 3b	62	0.8375	0.7977	37.74	0.000

Table 21: VIF results for Model 3b

Covariate	**VIF**	**1/VIF**
EventDriven	4.91	0.203818
RelativeValue	4.69	0.213087
StdDev3y	3.93	0.254320
GlobalMacro	3.92	0.255417
KIID5	3.86	0.259344
KIID6	2.29	0.436215
LongShort	1.98	0.504437
KIID4	1.93	0.517035
MarketCorr	1.47	0.678137
FixedFee	1.45	0.690397
KIID2	1.40	0.712743
PerformanceFee	1.34	0.745762
Mean VIF	2.76	

In table 22 we see that we now can reject the hypothesis of normally distributed residuals at a 5% significance level. This can also be seen in Figure 5 (see appendix) This is a decline from the previous model.

Table 22: Shapiro-Wilk test Model 3b

Covariate	**Obs**	**W**	**V**	**z**	$Prob. > z$
Res	62	0.94798	2.903	2.302	0.01068

5.4 Model 4 - Probabilistic regression model

For the probablistic model, a binary variable is defined, in the following way:

$$SharpeBin = \begin{cases} 1, & \text{if Sharpe ratio above 0} \\ 0, & \text{otherwise} \end{cases}$$

$$\begin{aligned} \Pr(SharpeBin_i| \\ &, \beta_1 StdDev3y \\ &, \beta_2 KIID2 \\ &, \beta_3 KIID4 \\ &, \beta_4 KIID5 \\ &, \beta_5 KIID6 \\ &, \beta_6 KIID7 \\ &, \beta_7 FixedFee \\ &, \beta_8 PerformanceFee \\ &, \beta_9 LongShort_i \\ &, \beta_{10} EventDriven_i \\ &, \beta_{11} GlobalMacro_i \\ &, \beta_{12} RelativeValue_i \\ &, \beta_{13} MarketCorr) \end{aligned} \tag{23}$$

In this model some covariates were able to predict the dependent variable perfectly and they were therefore omitted, which means that some observations were lost. This problem occurs commonly in probit models, in our case due to few observations. In other words, there are *variables* that have same the values for the exact same observations.

Table 23: Model 4 fit

Model	**Obs**	**Pseudo** R^2	**Wald** $\chi^2_{(8)}$	$Prob. > \chi^2_{(12)}$
Model 4	44	0.2638	275.68	0.000

Table 24: VIF results for Model 4

Covariate	**VIF**	**1/VIF**
EventDriven	7.18	0.139209
RelativeValue	7.12	0.140465
FixedFee	5.80	0.172272
StdDev3y	4.77	0.209539
GlobalMacro	3.72	0.268997
LongShort	3.27	0.305756
KIID3	2.55	0.391759
PerformanceFee	2.33	0.429406
KIID4	2.08	0.479827
KIID5	1.56	0.642521
NAV	1.16	0.861660
KIID7	1.08	0.928996
Mean VIF	3.55	

6 Empirical results

↪ *This section includes a summary of our empirical findings from the regression model estimates. The empirical results in this section be will discussed further in the analysis chapter of this thesis.* Table 25 shows the overall results of the regressions. In the first

model, all covariates are included. In later models we decide to split the $KIID$ covariate into 6 binary covariates, thus the binary covariates are not included in the first model. The first models exhibits an R^2 value of 0.7714 as well as an adjusted-R^2 value of 0.7598. Through modifications of the initial model, our final models are the two versions of Model 3. Model 3a displays a R^2 value of 0.8422 and an adjusted-R^2 value of 0.8371. Model 3b displays an R^2 of 0.8546 and adjusted-R^2 value of 0.8486. We increase the explanatory power of our model by almost 10 % through our modifications. In model 3a, we receive significant results that hedge funds on average decreases the Sharpe ratio by -0.65 units.

In our probabilistic regression model, *LongShort* and *GlobalMacro* has negative coefficients, which implies a low probability *increase* given that the hedge fund uses respective increase. Covariates *EventDriven* and *RelativeValue* have positive effects which indicates a *larger increase* in probability that the hedge fund has a higher Sharpe ratio than zero.

Table 25: Estimation results - Regression of covariates on Sharpe ratio

Model	Model 1	Model 2a	Model2b	Model 3a	Model 3b	Model 4
Covariate/Regressand	Sharpe	Sharpe	Sharpe	Sharpe	Sharpe	SharpeBin
StdDev3y	-0.0886873***	-0.0808696***	-0.301518**	-0.1348605***	-0.4259296**	0.0020571
	(-3.60)	(-3.30)	(-2.80)	(-4.89)	(-3.29)	(0.02)
MarketCorr	1.083685***	1.099638***	2.22478***	1.162484***	2.045231***	-
	(17.57)	(18.54)	(6.04)	(23.64)	(6.96)	-
NAV	-1.19e-06	-9.15e-07*	-1.72e-06	-	-	-
	(-1.81)	(-2.12)	(-1.53)	-	-	-
HedgeFund	-0.3552871	-1.374456	-	-0.6510698***	-	-
	(-0.40)	(-1.61)	-	(-4.53)	-	-
Domestic	0.1166947	0.1260265	2.261413	-	-	-
	(0.33)	(0.43)	(1.48)	-	-	-
Foreign	0.1406658	0.0808203	0.3630749	-	-	-
	(1.30)	(0.74)	(0.51)	-	-	-
FixedFee	-0.2249553	-0.2460037*	-0.8464283	-0.0896402	-0.2038869	-0.6155112
	(-1.85)	(-1.97)	(-1.80)	(-1.54)	(-0.85)	(-1.34)
PerformanceFee	-0.0148535	-0.0078674	-0.0669163	-	-0.0278279	-
	(-1.15)	(-0.61)	(-1.69)	-	(-0.92)	-
Leverage	0.2046391	0.5600269	0.0984143	-	-	-
	(0.28)	(0.73)	(0.14)	-	-	-
Age	-0.0002214	0.0015399	-0.1142134	-	-	-
	(-0.05)	(0.31)	(-1.40)	-	-	-
LongShort	-0.2315661	-	-0.5836172	-	-0.9962347**	-3.243185***
	(-0.52)	-	(-0.82)	-	(-3.02)	(-7.92)
EventDriven	-0.6182424	-	-0.8360751	-	-0.7081842*	1.36219**
	(-1.44)	-	(-0.82)	-	(-2.09)	(2.88)
GlobalMacro	-0.4447796	-	0.0893465	-	-0.04096	-3.603319***
	(-0.79)	-	(0.10)	-	(-0.06)	(-6.44)
RelativeValue	-0.0686492	-	-0.7795688	-	-0.0220514	1.203584**
	(-0.11)	-	(-0.86)	-	(-0.07)	(3.02)
Dividends	-0.0556113	0.0247364	-0.0786188	-	-	-
	(-0.30)	(0.13)	-0.16	-	-	-
OpenToPublic	-0.117407	-0.0831575	0.4441876	-	-	-
	(-0.38)	(-0.26)	0.51	-	-	-
KIID	-0.8726328***	-0.8585684***	-0.7906655	-	-	-
	(-3.82)	(-3.59)	-1.80	-	-	-
KIID2	-	-	-	6.243566***	4.623125***	-
	-	-	-	(3.79)	(4.40)	-
KIID3	-	-	-	1.174267*	-	-
	-	-	-	(2.31)	-	-
KIID4	-	-	-	0.4477293	-0.2367534	-1.133991
	-	-	-	(1.24)	(-0.56)	(-1.40)
KIID5	-	-	-	0.3246116	0.9306116	-1.60117
	-	-	-	(2.14)	(0.96)	(-1.38)
KIID6	-	-	-	-	1.455446	-
	-	-	-	-	(0.97)	-
KIID7	-	-	-	1.085083*	-	-
	-	-	-	(2.46)	-	-
Constant	6.979724***	6.738187***	7.519135**	2.166694***	5.191758***	6.319872***
	(4.62)	(4.48)	(2.86)	(4.88)	(3.77)	(6.48)
Observations	353	353	62	353	62	44
Adjusted R^2	0.7598	0.7519	0.6457	0.8380	0.7977	-
R^2	0.7714	0.7611	0.7387	0.8421	0.8375	0.2638⋆

t statistics in parentheses
* $p < 0.05$, ** $p < .01$, *** $p < .001$
⋆ pseudo R^2

7 Analysis

↪ *This section contains the analysis of the results, both the analysis of the regressions results in terms of numerics, as well as the econometric interpretation. We also discuss the results and connect the results to our theoretical framework, such as how our results go along with the effective market hypothesis and different threats to internal validity of the model.*

7.1 Econometric analysis

In the first model there was multicollinearity present between the $HedgeFund$ covariate and the strategy covariates. This could be seen in the VIF table where the values of the mentioned covariates were above the predetermined threshold, as well as in the correlation matrix presented in Table 5. Thereby, we decided to do two sets of regression models. One which would include the $HedgeFund$ covariate but not the strategy covariates and vice versa.

In the second model we used a stepwise regression method with the Bayesian Information Criterion and the Akaike Information Criterion to remove non-explaining covariates. Due to the fact that BIC penalizes non-explaining covariates harder, we conformed to BIC[15]. Initially when including all covariates we received with R^2 of 0.7714 and and adjusted-R^2 of 0.7598. We also found there was a high multicollinearity between some covariates. For instance, we recognized that most hedge funds have a KIID value of either 5 or 6, so accordingly, parts of the domain of KIID should be highly correlated with the hedge fund covariate which is a potential cause for multicollinearity. This was solved by dividing the KIID covariate into six different binary covariates, which was possible due to the rather limited domain of the KIID covariate. All other covariates were below the predefined threshold.

By analyzing the results of the regressions for models 2a and 2b, we could see that the covariates $domestic$ and $foreign$ were severely penalized by the BIC as well as when setting a tolerance p-value at 0.20. We found that this is due to that the covariates are not mutually exclusive. The funds can of course have both domestic and foreign investments. The covariate Age was also penalized by BIC, since removing the covariate generated a lower BIC value. We found this results counter-intuitive, since we believed that older funds in general should have a higher Sharpe ratio than new funds.

In the third model, we removed the covariates suggested by the BIC and also as previously mentioned divided our KIID covariate into six indicator covariates. We continued with two sets of regression models based on model 2. One where $HedgeFund$ acted as key independent covariate, and one where the strategy covariates were the key dependent covariates. Since Model 3a has 3 covariates less than Model 3a, we compared the adjusted-R^2. Model 3b has a slightly lower R^2 value at 0.8375 compared to Model 3a, with a R^2 of 0.8421. Since both versions of Model 3 are essential to explain whether hedge funds provide a higher risk adjusted rate of return in terms of Sharpe ratio, both versions are considered to be the final versions.

According to Model 3a, hedge funds generate a 0.6511 lower Sharpe ratio compared to mutual funds. This estimate is statistically significant at a 0.1 % significance level.

However, since we used the risk-free rate of return as the benchmark index for both fund types, this results can be questioned. The two fund types have different objectives, thus the results are not completely justified. However, due to lack of better ways to compare the funds, we use the risk-free rate of return as benchmark for both fund types.

Our fourth model uses a probabilistic regression model. This was our primary idea, since our thesis question aims to answer a yes/no question and we make an extensive use of binary independent covariates. Therefore the probit regression model suits the dataset very well. In Table 25 we can see that, all strategies are significant at the 1 % significance level. The probit estimates are negative for $LongShort$ and $GlobalMacro$ and positive for $EventDriven$ and $RelativeValue$. When applying the probit model, we wanted to conclude whether the probability increases/decreases of a higher Sharpe ratio given a the usage of a certain strategy.

We have throughout the models non-normally distributed residuals. This is most likely an effect of our limited number of observations. According to the central limit theorem having a large number of observations should make the residuals approximately normally distributed. Model 3a and 3b display more centralized residuals than the previous models. The reason for the steeper residual curve is either the exclusion or inclusion of covariates between the regression models, since these are the only aspects in which the models differ.

7.2 Threats to internal validity

When estimating regression models, there might be several threats to internal validity but also external validity. The threats that we have recognized are sample selection bias, omitted variables bias as well as simultaneous causality bias.

7.2.1 Sample selection bias

In our case, the sampling scheme was to include the total number of mutual funds, as well as all hedge funds in Sweden (including those not open to the public). The sample was based on the funds available on the 15^{th} of March 2014. The data includes returns and Sharpe ratio calculated for the preceding 3 years between 2011 and 2014. We estimate the Sharpe ratio for mutual funds and hedge funds. The problem that might occur is that the sample only includes funds that has survived all three years without defaulting. The solution to this problem would be to change the sample population from the funds that were available in March 15^{th} to the funds available in the beginning of of 2011, March 15^{th}, including defunct funds. However, due to the fact that failed funds are excluded from data, finding data on failed funds is often very hard, there is no simple way of resolving this issue. By not including failed funds, both positive and negative biases are possible. There must be data available on whether hedge funds or mutual funds are more prone to defaulting. Only then can we discuss whether the bias is over- or underestimated.

7.2.2 Omitted variables bias

There are few cases where omitted variable bias does not occur. In our regression models OVB is a particular issue, due to the fact that hedge funds are generally more reluctant to give out information about holdings, market exposure etc. This makes it harder to estimate why certain hedge funds outperform others. Variables that would improve our model would include a variable explaining market exposures, largest holdings, largest industry exposure etc.

7.2.3 Simultaneous causality bias

Simultaneous causality bias occurs when there is reverse causal effect from the causal effect that we are interested in. Such a bias might occur in our model through the correlation of the Sharpe ratio to the KIID covariates. Fund managers decide the classification of the funds KIID. The classification is based on the volatility of the fund. Therefore one might assume that the Sharpe ratio can have a causal effect on the KIID covariates. A solution to this problem would be to use more sophisticated regression methods such as the use of an instrumental variable. However, we strongly believe that the correlation should not be strong enough for a bias caused by simultaneous causality. The volatility of a fund changes frequently whereas the KIID stays constant if not an active decision is made on the core objective of the fund.

8 Adherence to Effective Market Hypothesis

↪ *In this section, we discuss how well hedge funds adhere to the effective market hypothesis. We compare and contrast our results to previous studies and finally conclude on whether Swedish hedge funds contradict the EMH.*

8.1 Empirical findings

By calculating the yearly return for the NHX, an equal weighted hedge fund index of hedge funds in Sweden, compared to AFGX (Affärsvärldens Generalindex), which is a stock market index for the Stockholm Stock Exchange and OMXS30, a capitalization-weighted index that consists of the 30 most-traded stocks in Sweden, we can easily see that there is no year after 2005 that the HFX generated higher returns than the corresponding stock market indices. However, we see during the financial crisis in 2008, the NHX loss was substantially smaller than the corresponding indices for the period. Also in 2011, when the stock markets fell due to fear of contagion of the European sovereign debt crisis to Spain and Italy, both stock market indices fell heavily, while the NHX index dropped less than three percent of their total holdings. In 2009, when the stock markets were recovering, we could see that the stock market were up by well over 40 %, whereas hedge funds performed around a third of the stock market returns. So for the period 2005-2013, hedge funds in general does not violate the efficient market hypothesis.

Table 26: Index for hedge funds and stock market

Year	NHX	AFGX	OMXS30
2013	6,58%	23,37%	20,66%
2012	4,86%	11,89%	11,83%
2011	-2,79%	-16,47%	-14,51%
2010	6,10%	23,15%	21,42%
2009	14,79%	48,10%	43,69%
2008	-6,89%	-42,06%	-38,75%
2007	1,10%	-6,82%	-5,74%
2006	7,26%	24,50%	19,51%
2005	10,1%	32,64%	29,4%

Our results are in accordance with the results of Dichev and Yu (2011). They find that annualized dollar-weighted returns are 3-7 % lower than the corresponding buy-and-hold funds, generally represented by mutual funds. Contrary to our results there are the results of Brown, Goetzmann and Ibottson (1999). They find that most off-shore hedge fund strategies manage to generate positive alpha, which would indicate a violation of the EMH. They recognize however in their research the high attrition of funds over the period 1989 to 1995. This has most definately influenced the true performances of the funds.

8.2 Inference

Our results contradict those of Brown, Goetzmann and Ibottson (1999). There are several possible explanations for this contradiction. The primary reason is how the research for Brown, Goetzmann and Ibottson (1999) was conducted. The benchmark selection was in favor of hedge funds since risk-free interest rate was used as a benchmark for hedge funds and indices for the mutual funds. Since hedge funds can buy, for example, stocks connected to any index, hedge funds can in theory have perfect correlation to an index. This would mean that hedge funds performs as a mutual fund but its performance is judged in relation to the, often significantly lower, risk-free interest rate.

Another reason for this contradiction could be the difference in time periods. Our results are based on data over the period 2011-2014, where the severe financial crisis has had a longlasting impact on the financial markets, whereas Brown, Goetzmann and Ibottson (1999) studies off-shore hedge funds based on data over the period 1989-1995. According to our results, we do not find that hedge funds violate the efficient market hypothesis, i.e. we do not find any evidence that hedge funds consistently outperform the market. However, this is not the objective for hedge funds either.

Hedge funds have the objective to generate absolute returns, and perhaps more importantly, achieve stable returns to a reasonable risk level, while having a low market correlation. Also, to say that hedge funds in general do not violate the effective market hypothesis is not the same as saying that are not some hedge funds manage to continuously outperform the market, which can be read more in detail in Fung and Hsieh (2011).

9 Preferred investment strategy

↪ *In this section, we discuss the preferred investment strategy from a hedge fund managers view. We determine the investment strategy most used and discuss underlying reasons based on conducted interviews.*

In order to answer the question whether there is an investment strategy that is used more frequently than others, we conducted two interviews with managers at two different hedge funds, Christian Carping at DNB and Ulf Berg and Krister Sjöblom at eTurn Fonder. Carping is the manager of a multi-strategy hedge fund and therefore he has an overbridging view of strategies. From his point of view, aside from being stable and profitable, hedge funds should also be market neutral. For him, as a manager of a multi-strategy fund, the correlation between both hedge fund strategies as well as between specific funds is important since the purpose of using a multi-strategy is to remove some of the risk by diversifying. Berg and Sjöblom run eTurn, which is a company with several hedge funds. The funds all use the same strategy, an event driven strategy based on quantitative computer models. Since they only use one strategy they have a less clasping view of hedge fund strategies and more of an in-depth view of event driven strategies. Since they do not have an objective view of strategies, the interview did not include questions about their preferred strategy and what they value in a strategy.

9.1 Inferences from interviews

During both interviews it was stated that hedge funds are fairly uncommon in Sweden and Carping states that it is hard to make a diversified multi-strategy fund in Sweden, which would indicate that there is an uneven distribution of hedge fund strategies. Our data suggests that long/short strategies are the most common and this is strengthened by the interview with Carping, in which he stated that Sweden is a "stock country" where it is relatively common for individuals to own stocks. This has, according to him, translated into a relatively large amount of mutual funds and it could also help explain the large amount of hedge funds using long/short strategies we have seen in our data.

Another potential cause for the relatively large amount of long/short hedge funds is that, according to Carping, small thresholds present for starting a stock-based (long/short) hedge fund. Our intution is also strengthened by Berg and Sjöblom who said that their strategy is fairly rare in Sweden. This is quite strange since Berg and Sjöblom states that Sweden and the Nordic area showcase properties suitable for event driven strategies. Though according to both interviews, event driven strategies, has had a hard time performing well since the financial crisis of 2008 when many of the event-driven went really well. This is, according to Carping (who decided not to invest in event driven strategies), an effect of the central banks decisions to "terminate" events and pushing down interest rates. Below we have the representation of hedge fund strategies in our dataset. Based on this the most common strategy is long/short which corresponds to 50.0 % of the hedge fund strategies. Which would indicate that long/short is the preferred strategy of hedge fund managers in Sweden.[6]

[6] `http://fondbolagen.se/sv/Studier/Studier/Fakta-8-av-10-svenskar-sparar-i-fonder/`

Table 27: Distribution of Hedge fund strategies

Strategy	Frequency
Long/Short equity	50.00
Relative Value	10.34
Event Driven	29.31
Global Macro	10.34
Total	100.00

Fung and Hsieh (2011) come to the conclusion that 20% of long/short strategies, in general, manages to generate significant alpha. Since this report do not have the same geographical limitations as this thesis it is hard to make a fair comparison. Also there is no reference to the performance of other strategies and therefore it is not fair to make a comparison based on this report. Olmo and Sanso-Navarro (2012) find that global macro strategies outperform the other strategies. Since their study is based, exclusively, on data from the financial crisis in contrast to our market neutral data it is only possible to draw conclusions for the performance during financial crisis. Since macro strategies analyze the movements of the market and make money by taking advantageous positions, while other strategies do not necessarily have this objective market view, this was to be expected. In other words, many of the other strategies focused on picking the winner in a sinking ship while global macro bet money on that the ship was going to sink.

When looking from Carping's perspective, the diversity in hedge fund strategies makes it possible for him to diversify his portfolio and there is no strategy that, in general, is to prefer. Since with only one strategy, funds like his would not exist. He said that globally, there is not that much of a difference between the return of specific strategies, it all depends on the fund manager. We could see a hint of this in Fung and Hsieh (2011), where 20% of the long/short hedge fund strategies performed very good even though they use the same strategy. This could mean that the Swedish preference of long/short strategies mostly comes from the cultural aspect and not from the a reputation as a high performing strategy.

From our other research the results has been inconclusive and we have not found a strategy that is to be preferred from a strictly performance point of view. It has also been hard to, with the help of previously conducted studies, come to a conclusion since they all give different perspectives. What can be said from these is that there is nothing to indicate that long/short should in any way stand out in terms of representation, with exception to the result of Fung and Hsieh (2011) which mention the performance of long/short but do not compare it to other strategies. This is in line with the results from both interviews. Since we have found nothing to indicate that long/short is the strongest strategy, we conclude that the long/short preference is a result of the stock-culture in Sweden.

10 Conclusions

By the use of a multiple linear regression model it has been shown that Swedish hedge funds do not generate as high risk-adjusted returns as Swedish mutual funds, when using the same benchmark. In regards to best performing hedge fund investment strategy in Sweden, the results have been inconclusive. Our results show that the long/short and global macro strategies tend to have a lower Sharpe ratio, and event driven and relative value strategies have a higher Sharpe ratio. We believe however that due to the low number of observations, one cannot fully conclude which strategy is the highest performing. Though data show that long/short strategies are preferred by Swedish hedge fund managers. The reason for this seems to be the stock culture in Sweden according to interviews with hedge fund managers. Also, by studying literature and index performances it has been shown that hedge funds do not violate the effective market hypothesis.

11 Future research

Hedge funds have been around for 50 years and have become more significant in playing the role of allocating capital in the financial markets in order to make it more efficient. Hedge funds have also become more important on the Swedish market, which can easily be seen, because of the growth of hedge funds in Sweden have on average been larger than worldwide. This leads to that in future research, more hedge funds can be included in order to get a greater reliability, but also validity. In order to successfully examine different investment strategies in contrast to market indices, the future research should be based more on monthly returns rather than yearly. In order to understand Swedish hedge funds more in depth, they should be compared on the global market for hedge funds, for instance with hedge funds based in New York and London, where hedge funds are more established. Also the traditional risk-measures for funds cannot be applied to hedge funds as well as to mutual funds. We also think that more research is needed towards finding appropriate methods for comparing hedge funds to mutual funds.

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Appendices

Table 28: Estimation results for Model 1

Covariate	Coef.	(Std. Err.)	t	$P > \|t\|$	[95 % Conf.	Interval]
StdDev3y	-.0886873	.0246484	-3.60	0.000	-.1371724	-.0402023
Beta	1.083685	.0616895	17.57	0.000	.9623371	1.205032
NAV	-1.19e-06	6.57e-07	-1.81	0.071	-2.48e-06	1.03e-07
HedgeFund	-.3552871	.890617	-0.40	0.690	-2.107194	1.396619
Domestic	.1166947	.3533783	0.33	0.741	-.5784255	.8118148
Foreign	.1406658	.1080845	1.30	0.194	-.071944	.3532756
FixedFee	-.2249553	.1213587	-1.85	0.065	-.4636764	.0137658
PerformanceFee	-.0148535	.0128903	-1.15	0.250	-.0402096	.0105025
Leverage	.2046391	.7405463	0.28	0.782	-1.252068	1.661346
Age	-.0002214	.00489	-0.05	0.964	-.0098403	.0093976
LongShort	-.2315661	.4487832	-0.52	0.606	-1.114354	.6512223
EventDriven	-.6182424	.4291792	-1.44	0.151	-1.462468	.2259833
GlobalMacro	-.4447796	.5657785	-0.79	0.432	-1.557706	.6681467
RelativeValue	-.0686492	.6432316	-0.11	0.915	-1.333931	1.196633
Dividends	-.0556113	.1884375	-0.30	0.768	-.4262812	.3150585
OpenToPublic	-.117407	.3072329	-0.38	0.703	-.7217558	.4869419
KIID	-.8726328	.2282994	-3.82	0.000	-1.321714	-.4235517
Constant	6.979724	1.510725	4.62	0.000	4.008021	9.951427

N=	353
$R^2 =$	0.7714
Adjusted-$R^2 =$	0.7598
$F_{(17,335)} =$	48.39

Table 29: Estimation results for Model 2a

Covariate	Coef.	(Std. Err.)	t	$P > \|t\|$	[95 % Conf.	Interval]
HedgeFund	-1.374456	0.8556641 -1.61	0.109	-3.057536	.3086239	
StdDev3y	-0.0808696	.0244957	-3.30	0.001	-.1290522	-.032687
KIID	-0.8585684	.2388817	-3.59	0.000	-1.328445	-.3886914
Domestic	0.1260265	.2902699	0.43	0.664	-.4449304	.6969835
Foreign	0.0808203	.109327	0.74	0.460	-.1342245	.295865
Age	0.0015399	.0049751	0.31	0.757	-.0082461	.011326
FixedFee	-0.2460037	.1246283	-1.97	0.049	-.4911458	-.0008616
PerformanceFee	-0.0078674	.0128841	-0.61	0.542	-.0332103	.0174754
Leverage	0.5600269	.7715346	0.73	0.468	-.9575712	2.077625
Dividends	0.0247364	.1955918	0.13	0.899	-.35999	.4094627
OpenToPublic	-0.0831575	.3196886	-0.26	0.795	-.7119808	.5456657
NAV	-9.15e-07	4.33e-07	-2.12	0.035	-1.77e-06	-6.42e-08
MarketCorr	1.099638	.0593265	18.54	0.000	.9829439	1.216333
Constant	6.738187	1.504122	4.48	0.000	3.7796	9.696774

N=	353
R^2 =	0.7611
Adjusted-R^2 =	0.7519
$F_{(13,339)}$ =	53.75

Table 30: Estimation results for Model 2b

Covariate	Coef.	(Std. Err.)	t	$P > \|t\|$	[95 % Conf.	Interval]
StdDev3y	-0.301518	.1076928	-2.80	0.008	-.5184224	-.0846136
KIID	-0.7906655	0.4383731	-1.80	0.078	-1.673594	0.0922632
Domestic	2.261413	1.532305	1.48	0.147	-.8248065	5.347633
Foreign	0.3630749	0.7173989	0.51	0.615	-1.081841	1.80799
Age	-0.1142134	0.0816212	-1.40	0.169	-.278607	0.0501802
FixedFee	-0.8464283	0.4712011	-1.80	0.079	-1.795476	0.1026195
PerformanceFee	-0.0669163	0.0395612	-1.69	0.098	-.1465966	0.012764
Leverage	0.0984143	0.700273	0.14	0.889	-1.312008	1.508836
LongShort	-0.5836172	0.7100794	-0.82	0.415	-2.013791	0.8465562
EventDriven	-0.8360751	1.019406	-0.82	0.416	-2.889265	1.217115
GlobalMacro	0.0893465	0.8542044	0.10	0.917	-1.63111	1.809802
RelativeValue	-0.7795688	0.9043143	-0.86	0.393	-2.600951	1.041814
Dividends	-0.0786188	0.5067876	-0.16	0.877	-1.099341	0.9421039
OpenToPublic	0.4441876	0.8706207	0.51	0.612	-1.309332	2.197708
NAV	-1.72e-06	1.12e-06	-1.53	0.132	-3.99e-06	5.41e-07
MarketCorr	2.22478	0.368227	6.04	0.000	1.483133	2.966428
Constant	7.519135	2.625172	2.86	0.006	2.231767	12.8065

N=	62
R^2 =	0.7387
Adjusted-R^2 =	0.6457
$F_{(16,45)}$ =	7.11

Table 31: Estimation results for Model 3a

Covariate	Coef.	(Std. Err.)	t	$P > \|t\|$	[95 % Conf.	Interval]
HedgeFund	-0.6510698	0.1437063	-4.53	0.000	-0.9337264	-0.3684131
StdDev3y	-0.1348605	0.0276035	-4.89	0.000	-0.1891539	-0.0805671
KIID2	6.243566	1.645457	3.79	0.000	3.00711	9.480022
KIID3	1.174267	0.5091886	2.31	0.022	0.1727417	2.175792
KIID4	0.4477293	0.3597703	1.24	0.214	-0.2599045	1.155363
KIID5	0.3246116	0.1517217	2.14	0.033	0.0261896	0.6230336
KIID7	1.085083	0.4417193	2.46	0.015	0.2162638	1.953903
FixedFee	-0.0896402	0.0581699	-1.54	0.124	-0.2040548	0.0247743
MarketCorr	1.162484	0.049165	23.64	0.000	1.065781	1.259187
Constant	2.166694	0.444013	4.88	0.000	1.293363	3.040025

N=	353
R^2 =	0.8421
Adjusted-R^2 =	0.8380
$F_{(9,343)}$ =	122.90

Table 32: Estimation results for Model 3b

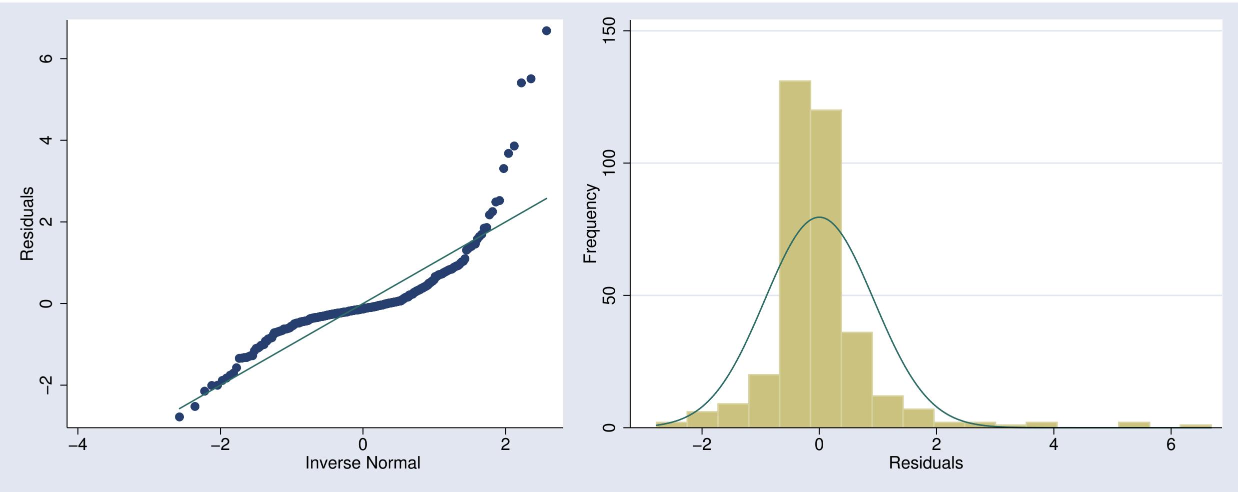
Covariate	Coef.	(Std. Err.)	t	$P > \|t\|$	[95 % Conf.	Interval]
StdDev3y	-0.4259296	0.1293458	-3.29	0.002	-0.6858596	-0.1659995
MarketCorr	2.045231	0.293932	6.96	0.000	1.454553	2.63591
FixedFee	-0.2038869	0.2385298	-0.85	0.397	-0.6832306	0.2754567
PerformanceFee	-0.0278279	0.0300977	-0.92	0.360	-0.0883114	0.0326557
LongShort	-0.9962347	0.3299765	-3.02	0.004	-1.659347	-0.3331222
EventDriven	-0.7081842	0.3389702	-2.09	0.042	-1.38937	-0.0269981
GlobalMacro	-0.04096	0.642233	-0.06	0.949	-1.331575	1.249656
RelativeValue	-0.0220514	0.3094425	-0.07	0.943	-.6438994	0.5997966
KIID2	4.623125	1.051607	4.40	0.000	2.509843	6.736408
KIID4	-0.2367534	0.4203494	-0.56	0.576	-1.081477	0.6079703
KIID5	0.9306116	0.9718288	0.96	0.343	-1.022351	2.883575
KIID6	1.455446	1.497302	0.97	0.336	-1.553495	4.464386
Constant	5.191758	1.37867	3.77	0.000	2.421217	7.962298

N=	62
R^2 =	0.8375
Adjusted-R^2 =	0.7977
$F_{(12.49)}$ =	37.74

Table 33: Estimation results for Model 4

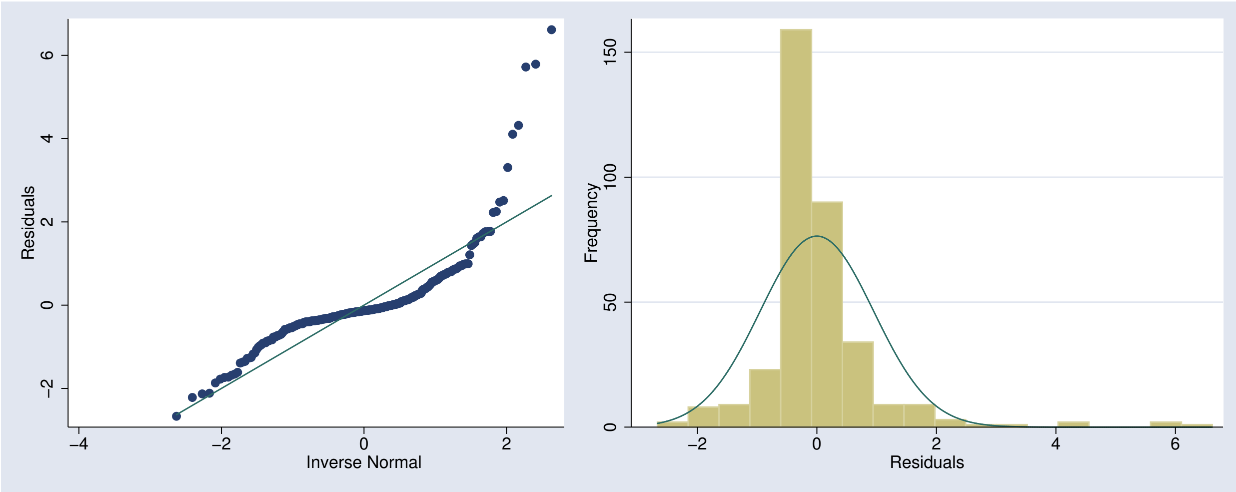
Covariate	Coef.	(Std. Err.)	z	$P > \|z\|$	[95 % Conf.	Interval]
StdDev3y	0.0020571	0.1210962	0.02	0.986	-0.2352872	0.2394013
KIID4	-1.133991	0.8104478	-1.40	0.162	-2.72244	0.4544569
KIID5	-1.60117	1.156647	-1.38	0.166	-3.868157	0.665816
FixedFee	-0.6155112	0.4594515	-1.34	0.180	-1.51602	0.2849972
LongShort	-3.243185	0.4092552	-7.92	0.000	-4.045311	-2.44106
EventDriven	1.36219	0.4734412	2.88	0.004	.4342626	2.290118
GlobalMacro	-3.603319	0.5594714	-6.44	0.000	-4.699863	-2.506775
RelativeValue	1.203584	0.3984289	3.02	0.003	.4226779	1.98449
Constant	6.319872	0.9746284	6.48	0.000	4.409635	8.230108

N=	44
Pseudo R^2 =	0.2638
Wald $\chi^2_{(8)}$ =	275.68



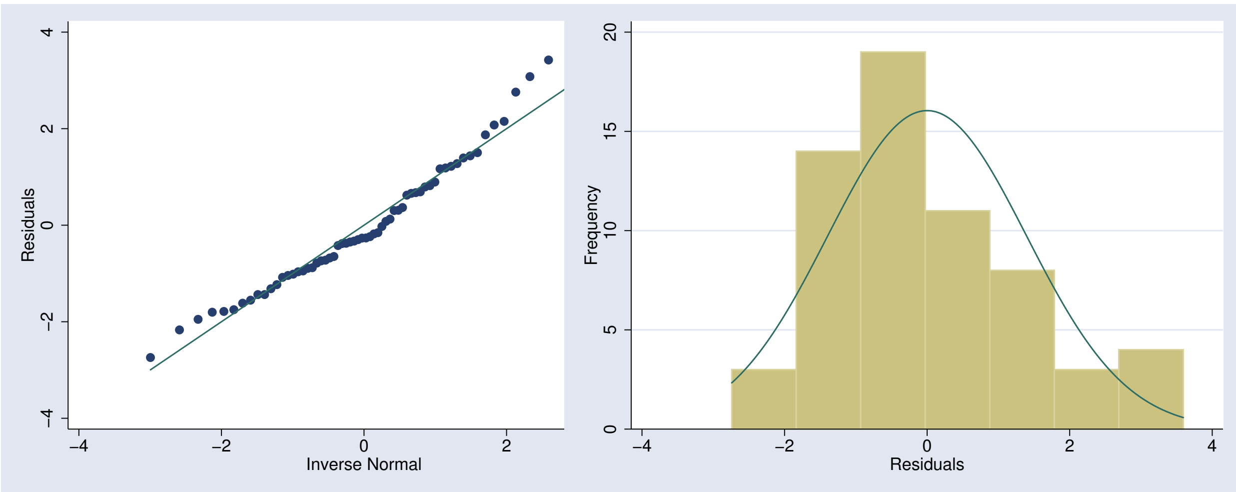
(a) Q-Q plot (b) Histogram

Figure 1: Residual plots for Model 1



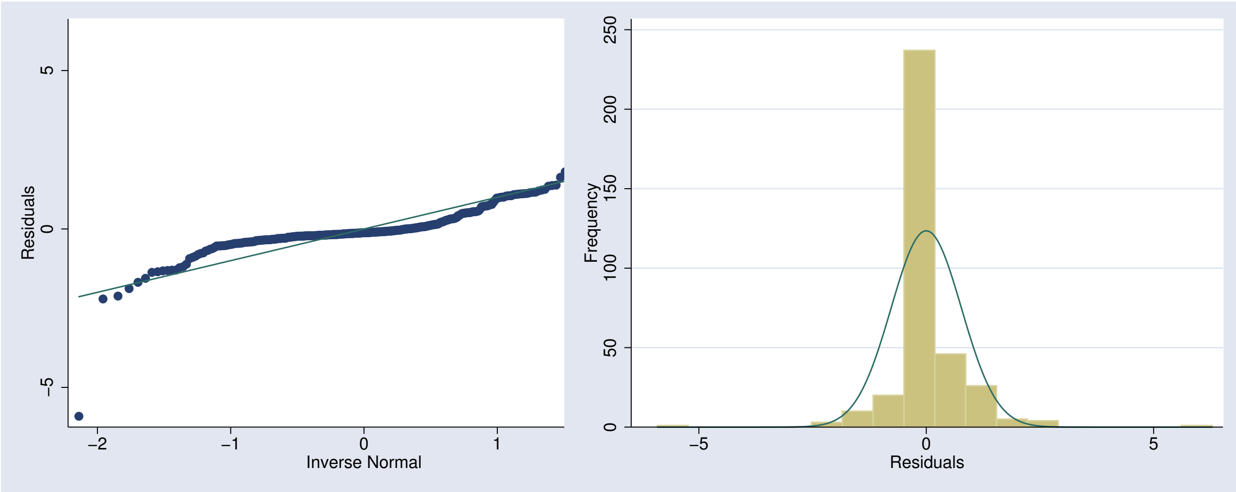
(a) Q-Q plot (b) Histogram

Figure 2: Residual plots for Model 2a



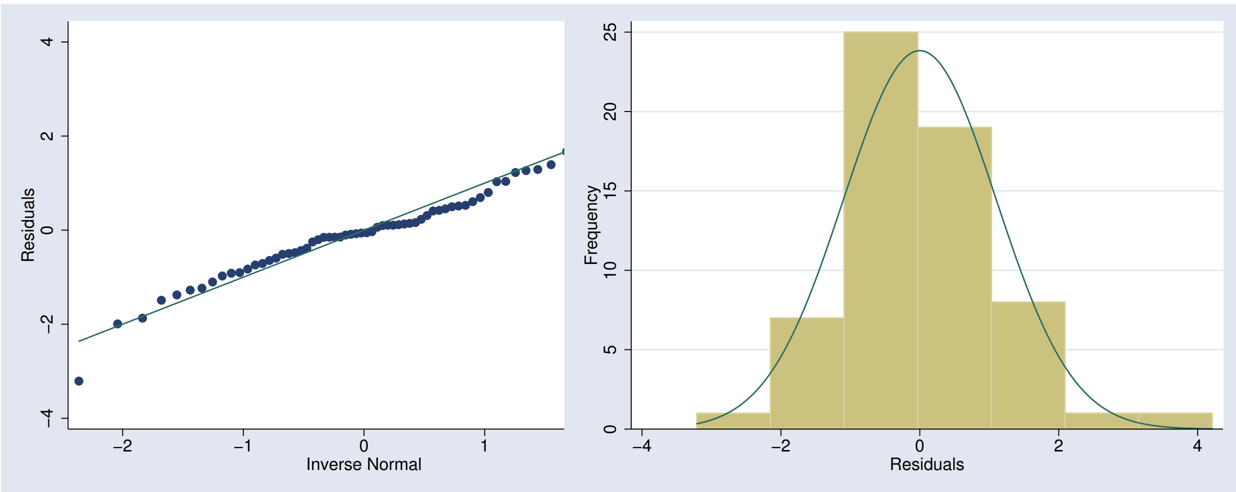
(a) Q-Q plot (b) Histogram

Figure 3: Residual plots for Model 2b



(a) Q-Q plot (b) Histogram

Figure 4: Residual plots for Model 3a



(a) Q-Q plot (b) Histogram

Figure 5: Residual plots for Model 3b

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