Stockholm School of Economics

Master's Thesis in Finance

High-Frequency Risk Exposures of Swedish Hedge Funds

JOHAN ESPINOSA*

ABSTRACT

From collected return data of 61 Swedish hedge funds, the capacity of several asset-pricing models to capture the risk exposure of the funds has been evaluated between June 2006 and September 2011. After testing more conventional models, a time-varying model inspired by Patton and Ramadorai (2011) has been constructed to capture the dynamic nature of hedge funds' risk exposure, using publicly available conditioning variables. It is found that the time-varying model offers better accuracy over constant models. Further, there is evidence of significant time-variation in the majority of the concerned hedge funds' risk exposure. An out-of-sample return estimation of the sample hedge funds has also been performed for the period 1990 to 2006 using the time-varying model.

Keywords: Swedish Hedge Fund, time-variation, risk exposure, beta, performance evaluation

Tutor: Magnus Dahlquist
Presentation Date: May 23rd, 2012

* 20427@student.hhs.se, espinosa.johan@gmail.com

Table of Contents

1. Introduction

1.1 Interest

Hedge funds claim to have an absolute return strategy and, because of loose regulation, have a vast freedom in taking dramatic positions. The spreading of High Frequency Trading has resulted in "speed wars", and managers attempt to maximize the speed and quantity of their automated trading. Hedge funds have widely engaged in this practice and have significant advantages due to the large costs of investment in such systems. Their positions can therefore radically change even during very limited lapses of time. A static analysis of hedge funds' risk exposure is therefore likely to miss the dynamic nature of their investments. The traditional asset pricing models have difficulties capturing these shifts properly, which in turn can lead to false interpretation of whether returns stem from a higher risk exposure or higher alpha, i.e. abnormal returns.

Fung et al (2008) recognise structural breaks in their study on the period from 1995 to 2004, resulting in different hedge fund risk exposures (or "betas") in different sub-periods. More recently, Patton and Ramadorai (2011) use a dynamic model to reveal strong evidence of shifting risk exposures in the hedge fund industry, much more than for mutual funds.

1.2 Purpose

Using collected return data from 61 Swedish hedge funds from 2006 to 2011, a range of different models are constructed in order to draw different types of conclusions concerning these investment vehicles.

The first purpose of this paper is to provide a picture of the performance of Swedish hedge funds. The returns of this type of investment vehicle are compared to the stock market, analysing and interpreting standard performance measures.

In a second phase, OLS regressions are conducted in order to construct models analysing the nature of hedge fund returns. The following pricing models have been applied to the data: the CAPM, the Fama-French 3-factor model, the Fung and Hseih 7-factor model and finally a similar model to Patton and Ramadorai (2011), that allows for time-varying risk exposures on a monthly and daily basis. The purpose of this step is to intend capturing the nature of hedge fund returns and underline how they are related to the sets of variable that define the models. The regression results in order to draw conclusions about how well the different models capture hedge fund returns.

Finally, the results stemming from the time-varying model are analysed. Evidences of time-variation in the risk exposure to the model's factors are revealed and argue for its importance when analysing hedge fund returns. Out-of-sample estimations of the hedge fund returns are also performed for the period 1990 to 2006, with a particular focus on two specific downturns in the 1990's. Finally, the limitations of model's accuracy for out-of-sample estimations are discussed.

This thesis is of a quantitative nature and of academic interest. Statistical tools are used to enlighten the dynamic aspect of hedge fund returns, a model that captures the time-variation in their risk exposure is proposed. The purpose of the thesis is therefore not to comment on individual funds' returns, positions, strategies or level of risk exposure.

2. Hedge Funds

2.1 History and Definition of Hedge Funds

The concept of Hedge Fund dates back to 1949, when Alfred Winslow Jones, a sociologist from Columbia University, introduced an investment strategy that consisted in protecting long investment in undervalued assets by shorting the stock of overvalued companies. Jones claimed attaining positive returns both in bullish and bearish environments, calling his strategy “market neutral” (Edwards (1999)). The concept of hedge funds has since then evolved to be associated with highly speculative and short-term investments.

Largely due to the lack of regulation, there is no exact definition of what constitutes a hedge fund. However, Koh et al. (2002), propose three common determinants for the majority of hedge funds: (a) they hedge the market to create market neutral positions, (b) fund managers earn performance fees, a percentage of the fund’s profits and (c) the managers invest own capital in their fund to ensure their commitment and alignment of interests with limited partners. Hedge funds appear mysterious as they are not required to communicate their results, and keep their investment strategy as their secret recipe. Although they have been widely criticized, not less so during the recent financial turmoil, hedge funds tend to show lower volatility and Value-at-Risk (VaR) than common asset classes (KPMG and AIMA (2012)).

2.2 Global and Swedish Hedge Fund Market

Hedge funds have received a great deal of attention in the last decades. They have become widely popular for their diversification benefits, and new funds have opened at a rapid pace. However, an opposite trend, more sceptical towards hedge funds, is growing. It has been vocalised amongst others by Simon Lack, a former JPMorgan banker, whose book “The Hedge Fund Mirage” is highly critical of the hedge fund industry. It is partly due to their large fees, but also their limited ability to deliver significantly better returns than cheap indices or trading strategies, as 60:40 stock bond portfolios. Critics can also be heard in Sweden, where for instance the pension fund AP7 decided in 2008 to stop investing in hedge funds to initiate a replication project, which was eventually abandoned. Richard Grottheim, CEO of AP7 since 2010, underlined at the time that alongside disappointing returns, hedge funds investments represented a “media risk”, having had exposure to collapsed US hedge fund Amaranth in 2006 (The Hedge Fund Journal). As a national pension scheme serving the Swedish population, AP7 evaluated that large resources would be necessary to defend to the public opinion their hedge fund investments, and decided to cut their allocation to these investment vehicles. Hedge funds have been widely debated and criticised by the public opinion for their role in the recent financial crisis, and governments look at imposing stricter regulation (for instance the upcoming Solvency II, Basel III and AIFMD in Europe) to prevent overly risky behaviours that would endanger the financial system. On the contrary, Boyson, Stahel and Stulz (2010) find in their recent study evidence that hedge fund performance is indeed affected by liquidity and funding shocks but the authors do not find evidence that hedge funds adversely affect liquidity or funding conditions on the market.

As of the first quarter of 2012, it is estimated that hedge funds globally managed an all-time high of US $2.13 trillion assets on behalf of their clients, representing roughly 1% of assets held by financial institutions. Hedge funds' assets have grown at an annual rate of 10% from US $700 billion on the third quarter of 2001. The majority of hedge fund investors are pension funds, insurance companies or other sophisticated institutions (Hedge Fund Research).

In Sweden, the hedge fund industry accounts for US $13.7 billion (SEK 95 billion) as of December 2011, approximately 5.3% of the total Swedish fund industry. It has grown by almost 70% since 2005, however in line with the average fund industry (Fondbolagens Förening).

2.3 Hedge Fund styles

More than 70% of hedge funds' assets under management are invested in equities, but managers use a range of different investment strategies, leading to very different funds altogether (Hedge Fund Research). There are no standards for the use of different strategy categories, and the databases collecting hedge fund returns use their own standards to classify hedge funds. For instance, Credit Suisse Tremont uses twelve different categories to build their different indices, while Hedge Fund Research uses four large categories leading to 33 sub-categories. These databases are large and count several thousand funds, which allows them to use fine-tuned categorisation. In this study, the style definition of Hedge Nordic is used, which divides hedge funds into five different categories. The limited sample size constrains us to use few categories, thereby allowing for a rougher classification.

The categories are the following:

1) Equity Strategies (equity and equity derivatives)

2) Fixed Income Strategies (fixed income and derivatives)
3) Multi Strategy/diversified Strategies (a fund is classified as Multi Strategy if less than 80% of the fund's activities comes from one particular classification category)
4) Managed Futures/CTA's (listed financial and commodity futures and foreign exchange, usually a systematic, i.e. model driven approach)
5) Fund of Hedge funds (funds that invest in other hedge funds)

2.4 On Hedge Fund Performance

Most research conducted on hedge funds is based on American data. It is by far the largest market for hedge funds, and there are large databases for their returns.

In a recent study, Joenväärä et al. (2012) meticulously merge databases in order to gather a large and representative compound of the hedge fund industry. They find that hedge funds on average add value, yielding 8.45% in excess return net of fees from 1994 to 2010. Similarly, using HFR (Hedge Fund Research) data of the period 1994-2011, a study conducted by KPMG and the Alternative Investment Management Association (2012) shows that the average hedge fund has delivered an annual return of 9.07%, beating stocks, bonds and commodities, while at the same time showing lower volatility and Value-at-Risk (VaR) than the other asset classes.

However, the main determinant for success in the hedge industry is the ability to deliver alpha, abnormal returns with respect to the risk a fund is taking.

Many studies indicate that although hedge funds seek to achieve a market neutral strategy, a significant proportion of the variation in their returns can be explained by market related factors (Fung and Hsieh (1997, 2001, 2002b, 2004a, 2004b)), and can to some extent be linearly replicated using existing investable assets (Hasanhodzic and Lo (2007)). This is a starting point in this thesis, as market factors are used as a basis to capture and analyse the returns of hedge funds.

Hedge fund returns have also been identified as partly non-linear in several studies (e.g. Fung and Hseih (1997, 2001), Agarwalk and Naik (2004)), which calls for the use of option-like variables to optimally capture fund returns. Fung and Hseih (2004b) construct a 7-factor model, which takes into consideration market factors but also Asset Base Style (ABS) factors as theoretical straddles portfolios. This model has since then been the most widely used and accepted model in hedge fund performance evaluation studies (Joenväärä et al. (2012)).

In Fung et al. (2008), the authors apply the 7-factor model on fund-of-funds. The authors consider them as an appropriate sample to study hedge fund returns as they are composed of a large selection of funds thereby mitigating some well-documented biases in the field. From 1994 to 2004, the authors find that fund-of-fund returns are largely driven by their exposure to the 7 factors in their model. Controlling for these exposures, they conclude that the average fund-of-fund does not deliver significant alpha, except for the period between October 1998 and March 2000. However, a handful of successful funds consistently manage to generate alpha over longer periods, proving large disparities between different fund managers. The absence of alpha for the average fund-of-fund can possibly be explained by the fees collected by managers (a common problem of "double fees" specific to the fund-of-fund industry).

Using their merged database, Joenväärä et al. (2012) analyse an equally weighted portfolio of hedge funds and conclude that it delivers a significant alpha of 5.87% per year during the period 1994-2010, also using the Fung and Hseih 7-factor model as a benchmark. A novelty in their research is the meticulous merging of databases, creating one of the largest and most rigorous samples in hedge fund research.

Finally, hedge fund returns are non-normal, implying several important features.

The significant left-tail risk (larger possible losses than possible gains) results in an underestimation of the tail losses in the traditional mean-variance framework (Agarwalk and Naik (2004)). Further, Brooks and Kat (2002) find that hedge fund returns are skewed (asymmetric) in their distributions. It implies that comparing Sharpe ratios of hedge funds will not give a perfectly accurate picture of their real risk-return performance. However, because of its easiness of interpretation, the Sharpe ratio is widely used in the industry.

2.5 Biases

There are some well-documented biases in hedge fund research (Fung and Hseih 2002a, 2009). As private investment vehicles, hedge funds are in most countries not compelled by law to publish their results. However, Swedish registered hedge funds do have the obligation to publish their results, which mitigates and in some cases completely rules out the validity of these biases on Swedish data.

2.5.1 Selection Bias

Private databases as TASS and HFR contain returns from funds managers whom voluntarily share their return information. This leads to a certain selection of returns that do not perfectly represent the industry as a total.

Investors of all kinds use the forenamed databases to a great extent when considering new investment opportunities, comparing historical returns and properties of the different funds. In turn, hedge fund managers want to appear on the databases for marketing purposes, in order to get investor exposure and be able to attract new capital for their funds. Managers with a satisfactory track record will want to share their results with potential new investors. On the other hand, fund managers with a poor track record will use other ways to make their funds appear attractive, as actively seeking to meet potential investors in order to explain their performances, or stress other aspects than their historical returns. This will lead to an overestimation of the industry's returns in the databases.

Moreover, funds that are overcommitted and do not need capital, be they successful or not, do not have any incentive to disclose their returns and are therefore not likely to share their results with the databases, further tweaking the representative nature of returns presented by databases.

2.5.2 Survivorship Bias

The databases providing fund information report predominantly existing and active funds, which are the most important ones for investors to make their decision. The funds that have abruptly ceased to operate, which have in general worse results than surviving funds, are often purged from the databases, leading to an overestimation of the industry's returns as a total.

This survivorship bias has been estimated by Brown, Goetzmann and Ibbotson (1999) on offshore funds as well as by Fung and Hseih (2000) to be around 3% per year.

2.5.3 Instant-History Bias

When a manager decides to disclose the fund's returns to a database, its past performance is also directly published. In general, managers of recently started funds forego an incubation period to construct a track record before joining. If the returns are good, the manager will disclose the past results and continue the fund; otherwise, the fund will be closed down and its results will remain unpublished. As the databases backfill the fund return information, there will generally be an upward bias in those databases. Fung and Hseih (2000) have estimated this bias at 1.4% per year.

3. Theoretical Framework

To analyse the return of Swedish Hedge Funds, several different frameworks and pricing models established in academic research are used.

3.1 CAPM

The starting point is the Arbitrage Pricing Theory (APT), according to which an asset's excess returns can be modelled as a linear function of a set of observable explaining variables. A single-factor model admits only one explaining variable as the source for return, to which assets are exposed:

$$r_{i,t} = \alpha_i + \beta_i f_t + \varepsilon_{i,t}$$

where $r_{i,t}$ is the excess return of asset i at time t

f_t is the excess return of the single-factor

β_i is the factor loading, or risk exposure

$\varepsilon_{i,t}$ is the error term

The single-factor Capital Asset Pricing Model (CAPM) was developed by Sharpe (1964), Lintner (1965), and Black et al. (1972), in which the factor is the excess market return. This model has been widely used as a benchmark for asset pricing. According to the CAPM, an asset's excess return depends on its exposure to the expected market portfolio excess return (ERM), the difference between the expected market portfolio return and the risk-free rate. In the CAPM, there is no return that is not explained by the market, and hence does not recognise any alpha.

Although the CAPM is based on strong assumptions, it has some empirical proof, mainly in the pre-1969 period (Bodie et al. (2008)).

3.2 Fama-French

As the CAPM shows some empirical contradictions, Fama and French (1992, 1993) expand the factor model to recognise two additional factors, namely the Small Minus Big (SMB) and High Minus Low (HML) factors. They come from previous research on the size effect by Banz (1981), that recognised an anomaly in the CAPM as stocks from small companies tended to over-perform larger companies, a difference in performance that is not captured in their market exposure (the stock's beta). Indeed, small-sized companies are often less covered by analysts, generally leading to an undervaluation of their stocks. The SMB factor is the return difference between a portfolio of small stock and a portfolio of large stocks, which is the return an investor can generate by taking a long position in small stocks and a short position in large stocks.

Stattman (1980) and Rosenberg, Reid and Lanstein (1985) find a positive relation between U.S. stock returns and the firms' book value of common equity to their market value. Fama and French therefore elaborate the high-minus-low factor, a return that depicts the better risk-adjusted performance of Value stocks (high book-to-market ratio) compared to Growth stocks (low book-to-market ratio).

The Fama-French asset-pricing model is captured by the following formula:

$$r_{i,t} = \alpha_i + \beta_{i,ERM} ERM_t + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \varepsilon_{i,t} .$$

3.3 Fung and Hseih

Researchers in the hedge fund field have early on recognised the necessity to incorporate some option-like returns to assess the performance of hedge funds. Indeed, hedge funds aim for absolute returns and many take long-short positions as well as use a wide range of derivatives to hedge their positions. Fung and Hseih (2004b) therefore construct an "Asset Based Style" (ABS) 7-factor model that captures both market related swings as well as option like returns in form of three "lookback straddles". These factors are intended to cover the differences in hedge funds' investing styles and strategies.

3.3.1 Market Long-Short Factors

Hedge funds taking long and short positions on the equity market have been shown to possess statistically significant exposure to the equity market (Fung and Hseih (2004b)). Therefore, the authors use two market related factors in their model: the return on the S&P 500 and a size spread return. Long-short hedge funds are expected to have, over time, a positive (even if generally low) exposure to the equity factor. Concerning the size spread factors, long-short hedge fund have a tendency to be long small stocks and short large stocks, as the previous generally offer better risk-adjusted returns than the latter.

The long-short factors of the Fung and Hseih model are the following:

$$ABS_{equity\ market,t} = R_{S\&P\ 500} - R_f = r_{S\&P\ 500}$$

$$ABS_{size\ spread,t} = R_{Russell\ 2000} - R_{S\&P\ 500} = r_{SMB}$$

3.3.2 Fixed Income Factors

Fixed income funds are significantly exposed to interest rates and spreads. Therefore, the authors have constructed two factors to capture their trading strategies, the yield spread of the 10-year Treasury bond over the risk free rate and the change in the yield spread between the 10-year treasury and Moody's Baa bonds.

$$ABS_{fixed\ income\ yield,t} = y_{10-y,t} - R_f$$

$$ABS_{fixed\ income\ spread,t} = \left(y_{Moody's\ Baa,t} - y_{10-y,t}\right) - \left(y_{Moody's\ Baa,t-1} - y_{10-y,t-1}\right)$$

3.3.3 Trend Following Factors

Trend-following hedge funds bet on big movements on the stock market, and usually generate higher returns in periods of volatility, be it good or bad times. Fung and Hseih have identified a portfolio of lookback straddles that present similar option like returns. A lookback straddle is a theoretical portfolio constructed to capture the maximum value of a trend-following strategy. It is composed of a call and a put option with strike prices equal respectively to the lowest value and highest value of the underlying under a given period. Fung and Hseih use the excess return of three different lookback straddles on bonds, currencies and commodities.

$$ABS_{trend-following\ bond,t} = R_{bond\ lookback\ straddle,t} - R_f$$

$$ABS_{trend-following\ currencies,t} = R_{currencies\ lookback\ straddle,t} - R_f$$

$$ABS_{trend-following\ commodities,t} = R_{commodities\ lookback\ straddle,t} - R_f$$

The 7-factor model is an aggregation of all the style-factors:

$$r_{i,t} = \alpha_i + \sum_{j}^{7} \beta_{j,i} ABS_{j,i,t} + \varepsilon_{i,t}$$

3.4 Patton and Ramadorai

Ferson and Schadt (1996) identify the common problem of time-variation in risks and risk premiums in the mutual funds industry. The authors' starting point is the realisation that managers of actively managed funds adapt their trading strategy to the market conditions, inducing a shift in their exposures. For example, in a bearish market, managers tend to shift their holdings away from stocks to more stable assets such as bonds. Traditionally, the performance of portfolios was assessed using unconditional expected returns as a baseline: the alpha of a portfolio was calculated using the risk free rate, the market excess return and a fixed market exposure, beta. As a result, using public information to shift risk exposure towards more stable assets in a bearish market is confounded with a superior performance of the manager, resulting in a better implied performance and alpha generation. However, the authors postulate that a strategy that can be replicated using public information should not be judged as superior. Therefore, they advocate controlling for this kind of common variation detectable in public information to perform a conditional performance evaluation. They propose using economically relevant conditioning information to dynamically adjust the true level of risk exposure of mutual funds to the factors in their model over time.

Patton and Ramadorai (2011) use the methods presented by Ferson and Schadt to analyse the hedge fund industry, which is even more subject to high-frequency dynamic trading strategies and shifting risk exposure than mutual funds. They take the analysis further and introduce a model that takes into account daily variations in risk exposures by applying daily conditioning variables to monthly hedge fund data. They find evidence of time-variation in the risk exposure of hedge funds, and postulate that allowing for monthly and daily time-variation of risk exposure increases the accuracy of the models with respect to constant models as the Fung and Hseih 7-factor model.

4. Time-Varying Model

4.1 Model

By following Patton and Ramadorai (2011), a factor model that allows for a time-varying risk exposure, i.e. a time-varying beta has been constructed. Consider a single-factor model, where the beta is dependent on some conditioning variable Z in the following way:

$$r_{i,t} = \alpha_i + \beta_{i,t} f_t + \varepsilon_{i,t} , \tag{1}$$

$$\text{where} \quad \beta_{it} = \beta_i + \gamma_i Z_{t-1}. \tag{2}$$

The conditioning variable Z has a zero-mean, implying that over the estimation period,

$$Average(\beta_{it}) = \beta_i .$$

By combining equations (1) and (2), we obtain:

$$r_{it} = \alpha_i + \beta_i f_t + \gamma_i f_t Z_{t-1} + \varepsilon_{it} , \tag{3}$$

which can be estimated using a OLS regression. In this model, forcing γ_i to be equal to zero would give us a traditional constant risk-exposure model. Therefore, we can test the significance of time-variation for fund *i* with the following Wald test:

$$H_0 : \gamma_i = 0 \qquad \text{vs.} \qquad H_0 : \gamma_i \neq 0 .$$

The model is expanded to capture daily variations, where the daily beta depends on monthly and daily information contained in the conditioning variable:

$$\beta_{i,d} = \beta_i + \gamma_i Z_{d-1} + \delta_i Z^*_{d-1} , \tag{4}$$

where β_{id} is the daily beta, Z_{d-1} is the monthly information of the conditioning variable (therefore constant throughout the month, and jumping to another value at the beginning of the following month), and Z^*_{d-1} is the daily information of the conditioning variable.

The daily return of such a model is as follows:

$$r^*_{i,d} = \alpha_i / n_t + \beta_{i,d} f^*_d + \varepsilon^*_{i,d} , \tag{5}$$

where r^*_{id} is the return on day *d* of the fund *i*, α_i is the monthly alpha, n_t is the number of days in month *t* (thus α_i / n_t being the daily alpha), and f^*_d is the factor on day *d*.

By replacing $\beta_{i,d}$ in equation (5) by equation (4), we obtain:

$$r^*_{i,d} = \alpha_i / n_t + \beta_i f^*_d + \gamma_i f^*_d Z_{d-1} + \delta_i f^*_d Z^*_{d-1} + \varepsilon^*_{i,d} \tag{6}$$

In this model, log returns for the factors are used, which implies that the fund's monthly return is equal to the sum of its daily returns during that month:

$$r_{i,t} = \sum_{d=1}^{n_t} r^*_{i,d} .$$

By summing up equation (6), we obtain:

$$r_{i,t} = \alpha_i + \beta_i f_t + \gamma_i f_t Z_{t-1} + \delta_i \sum_1^{n_t} f_d^* Z_{d-1}^* + \varepsilon_{it} \,. \quad (7)$$

It has to be noted that in equation (7), the dependent variable $r_{i,t}$ is the monthly return of fund i, and that all the variables on the right hand side are measured on a monthly basis. The variable $\sum_1^{n_t} f_d^* Z_{d-1}^*$ is a monthly aggregate of a daily interaction term, which captures variation in hedge fund risk exposure at the daily frequency.

Under the assumption that the error terms are serially uncorrelated, OLS regressions can be used, accounting for possible heteroskedasticity and non-normality of the residuals by using White robust standard errors.
The conditioning information is lagged so that the estimated alphas can be interpreted as an abnormal performance given the public information signals.

Hedge fund returns are for the most part only available on a monthly basis, the regression coefficients in equation (7) are estimated in a first place, which are then used in equation (6) as to obtain the daily model.
Again, we obtain a constant risk exposure model in equation (7) by forcing the coefficients γ_i and δ_i to be equal to zero. We can test the significance of time-varying risk exposure with the following hypotheses:

$$H_0 : \gamma_i = \delta_i = 0 \qquad \text{vs.} \qquad H_0 : \gamma_i \neq 0 \; and \; \delta_i \neq 0 \,. \quad (8)$$

We can also examine whether there is evidence of daily variation in hedge fund risk exposure by testing that the coefficient of the daily interaction term is zero:

$$H_0 : \delta_i = 0 \qquad \text{vs.} \qquad H_0 : \delta_i \neq 0 \,. \quad (9)$$

4.2 Factors

In order to construct the model, the Fung and Hseih 7-factor model has been used as a starting point. As mentioned previously, the 7 factors are three lookback straddles constructed by the authors (fixed income, commodities and currency), an equity market factor, a size spread factor, a bond market factor and a credit spread factor.
However, as the lookback straddles are unavailable on a daily basis, these factors cannot be used in the construction of the daily model and are therefore ruled out.

Building on the knowledge from Patton and Ramadorai (2011), using the full set of the remaining four factors does not add significance to the model. Further, in the time-varying risk exposure model, additional factors duplicate the number of variables in the OLS regression leading to less robust results (one extra factor leads to a total of 3 new regression variables). Patton and Ramadorai (2011) use the Bayesian Information Criteria (BIC) to determine which two of the four factors add more relevance to their model.

When comparing the factors according to the BIC on the sample data, it is found that 33 of the 61 hedge funds recognise the equity factor and the size factor as the most valuable. For the other funds, the preferred factors only showed a slight improvement compared to the most commonly selected factors. For an easier comparison and interpretation of the regressions results, the equity and the size factors are jointly selected for all funds.

The Stockholm OMX 30 has been chosen as the equity index. Even though many Swedish-registered hedge funds do trade globally, the majority of their investments are conducted on the Swedish market, which calls for a Swedish equity index.

It should be noticed that excess returns are used in the models, using the 3-month Swedish government bond as a proxy for the risk free rate.

The S&P Swedish Small Cap and the OMX 30 have been chosen to construct the size-spread factor.

4.3 Conditioning Variables

The conditioning variable Z will effectively introduce time-variation in the risk exposure. Daily interaction variables that capture the change in the risk exposure of the fund within the month need to be identified. The conditioning variables are chosen to make economic sense, i.e. can reasonably be identified as impacting managers' investment decisions and exposure to the risk factors.

Out of the set of 19 different conditioning variables that Patton and Ramadorai (2011) have empirically tested, they identify the four best ones, belonging to the following categories: volatility, performance, liquidity, and funding and leverage. The four different variables will in turn give four different time-varying models.

4.3.1 Volatility

When markets are volatile, it is likely that funds managers will want to keep their funds' volatility constant. In order to achieve this, they will have to cut their exposure to the market. It can be particularly accurate in the case of hedge funds as they strive for "absolute" returns, loosely correlated to the market. The conditioning variable VIX has been chosen. It is calculated from the price of options on the S&P 500, and is generally accepted as a measure of volatility.

4.3.2 Performance

When equity market indices deliver large returns, due to favourable market conditions, it is highly likely that hedge fund managers will increase their exposure to such indices. Even if the managers aim for absolute returns, they will not be too keen on underperforming cheap indices and will thus be likely to increase their exposure. The S&P 500 is chosen as a conditioning variable. It is important to note that the Fung and Hseih model already incorporates an equity factor. However, in this case, the S&P 500 as a conditioning variable will affect the effective risk exposure beta and only indirectly the total return of the model. It is also lagged one period, ruling out "double counting" in the model.

4.3.3 Liquidity

Both Aragorn (2005) and Sadka (2009) show that liquidity is an important determinant for hedge fund managers. Indeed, when liquidity rises, managers will be likely to enter and exit positions more frequently, leading to a higher risk exposure to market factors. Amongst others, Garleanu and Pedersen (2009) propose as a liquidity measure the TED spread, that is the difference between the 3-month LIBOR and the 3-month T-Bill. In this study, the LIBOR minus the Swedish 3-month Treasury Bill has been used.

4.3.4 Leverage

Finally, as hedge funds usually take on substantial leverage, their exposures will be likely to shift according to the quantity of leverage available, which is in turn dependent on the cost of borrowing. The change in the Swedish 3-month Treasury Bill, which is referred as "dLevel", has been chosen as the last conditional variable.

5. Data:

Hedge funds in Sweden fall under the law of "special funds" (specialfonder) and are as such required to disclose their monthly returns, net of fees, to Finansinspektionen, the Swedish Financial Supervisory Authority. They are also required to report a concentration measure, their absolute exposure towards their five largest investments in relation to the fund size, as well as return standard deviation.

Every month, Finansinspektionen publishes a PDF on its website providing the returns and concentration for all the special funds. The first data sheet is from December 2005. However, there is no available data for the months of April and May 2006, so data starting in June 2006 until September 2011 has been collected.

The information has been turned into a database of historical returns for a total of 402 different special funds.

As mentioned before, hedge funds are considered as a category of special funds, but all special funds are not hedge funds. I have therefore selected only hedge funds from the database. To differentiate hedge funds to other special funds, I have contacted MoneyMate and received a list of all active hedge funds registered in Sweden. I have also crosschecked with the Morningstar database to make sure the list was exhaustive.

As special funds are required to publish a factsheet about their fund, I have also verified the remaining special funds contained in the database to rule out any omission. If the fund manager did not explicitly state that the concerned fund was a hedge fund, I examined the factsheet of the fund and used several criteria to qualify the fund as a hedge fund:

- The fund must state that it is striving for absolute returns
- It must have a performance based compensation for the General Partner (typically, 2/20)
- It should not be a variant of another fund in the database (e.g. same fund using extra leverage)
- It should not have missing data during the concerned period
- It should have at least 24 months of data

If a fund's returns are missing for one or more periods from Finansinspektionen, it has been intended to complete the information by contacting the fund.

As a total, I have collected the returns of 61 hedge funds with a maximum of 64 months of data, and an average of 56 months of data per fund. The total number of observations is 3436.

The Swedish Hedge Fund returns from Finansinspektionen constitute a good sample, robust to the many biases of hedge fund research. As opposed to larger “voluntary” hedge fund return databases as HFR or TASS, Finansinspektionen collects the returns of *all* Swedish-registered hedge funds, which theoretically eliminates the risk for selection bias (when the manager chooses whether or not to publish the fund’s results). At the same time, it also eliminates any risk of instant history, as all returns are collected from the very inception of the fund, and of survivorship bias, as the fund returns are not purged from the database at closing.

Finally, when available, I have verified the data from Finansinspektionen on the fund managers’ website. Several errors have been spotted in the Finansinspektionen return database, most commonly (but not exclusively) sign errors (i.e. Finansinspektionen reporting a monthly return of 1.0% when the actual return was -1.0%). In case of discrepancy, the fund manager’s reported return have been chosen.

It is very uncommon that hedge funds publish their daily returns. However, I have encountered daily data for 9 of the 61 hedge funds in a Handelsbanken database. Naturally, it has been made sure that this data was consistent with the funds’ monthly returns collected from Finansinspektionen. This data will be used in order to support the methodology put forward in this paper, and reveal evidence that reliable daily risk exposures can be derived from monthly data.

6. Results

6.1 Return Analysis

The hedge fund returns that constitute the sample are largely heterogeneous. The following table describes the yearly return of the Swedish hedge funds from June 2006 (or from their inception) to December 2011

Table I: Annual return statistics of sample hedge funds and OMX 30

Category	Q1 Funds Returns	Avg. Return	Q3 Funds Returns	Avg. St. Dev.	Avg. Downside risk	Avg. Sharpe	5% VaR	Market Corr.	Nb of Funds
Equity	-1.3%	1.9%	4.3%	9.9%	6.8%	0.31	5.3%	0.27	21
Fixed Income	-0.6%	3.1%	5.9%	6.1%	3.8%	0.33	2.9%	-0.01	7
FoF	0.1%	1.2%	2.6%	5.1%	3.7%	-0.09	2.4%	0.48	15
Multi	1.2%	4.0%	7.4%	7.1%	3.9%	0.23	3.1%	0.19	7
Managed Futures	0.1%	3.3%	5.9%	11.4%	7.6%	0.18	5.3%	0.14	11
ALL	-0.4%	2.4%	4.0%	8.2%	5.5%	0.20	4.1%	0.26	61
OMX 30	n.a.	0.7%	n.a.	19.4%	14.4%	0.04	12.1%	1.00	n.a.

"Q1 Funds Returns" represents the annual compounded return of the 25th percentile worse performing funds during the period. "Avg. Return" is the average compounded return across funds by strategy. For the OMX 30, it is the compounded return. "Downside Risk" is a measure of volatility capturing only negative returns. The Sharpe ratio is a measure of the excess return per unit of volatility (standard deviation) "5% VaR" is the monthly Value-at-Risk with 5% confidence.

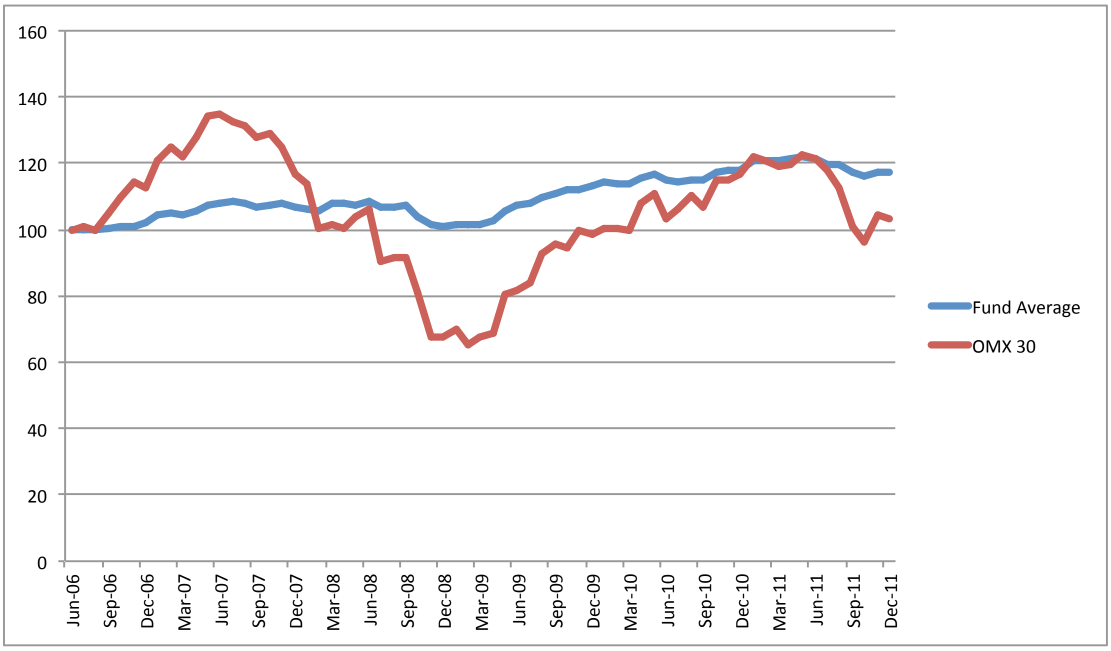
Because of the tremendous instability on the markets during the concerned period, the OMX 30 had a very low Sharpe ratio of 0.04, due to a close to zero compounded excess return. In that light, hedge funds in general have delivered higher risk adjusted returns, with an average Sharpe ratio of 0.20 as can be seen in Table I.

While the standard deviation incorporates the deviation form the average of both positive and negative returns, the downside risk is a volatility measure that captures only negative excess returns, which is the kind of volatility that investors are more averse towards. While the OMX 30 had a standard deviation of 19.3% during the period, it had a downside risk of 14.4%, figures that are substantially higher than those for hedge funds reported in Table I.

Even though hedge funds claim to deliver absolute returns, it appears that the average fund is somewhat correlated to the stock market over the studied period, as many researchers have already established. This is a crucial element for the following section, as return models using amongst others stock market returns are used.

A Fund Average Index has been constructed, as an equally weighted average of all hedge fund returns, which is a return indication of the average hedge fund.

Figure I: Evolution of the Fund Average Index and the OMX 30, Jun 2006 to Dec 2011



From Figure I, one can see that the average Swedish hedge fund seems to be less volatile than the Swedish equity index. Although they were struck by the financial crisis that started in 2007, Swedish hedge funds were much more resilient than the OMX 30 to the downturn until 2009. From its highest point in May 2007, the market had lost 51% in January 2009, while the average hedge fund lost around 6% during the same period.

Table II: Year-by-year average returns across hedge fund strategies

Year	Equity	Fixed Income	FoF	Multi	Managed Futures	ALL	OMX 30
2006	10.9%	3.6%	5.4%	9.7%	7.5%	7.9%	38.7%
2007	-0.6%	-1.2%	3.2%	2.7%	3.4%	1.3%	-5.7%
2008	-5.5%	4.2%	-9.5%	-1.2%	-2.5%	-4.1%	-38.8%
2009	15.9%	7.2%	8.5%	14.2%	17.9%	13.3%	43.7%
2010	6.7%	4.1%	4.6%	3.2%	9.0%	5.8%	21.4%
2011	-4.8%	3.0%	-1.6%	0.4%	-4.8%	-2.5%	-14.5%

Table II breaks down the average returns of the different strategies and the OMX 30 by year. Again, the average hedge fund returns appear significantly less volatile than stock market returns, yielding smaller downfalls in bearish times but also showing less potential during bullish periods.

6.2 Applying the Models

In a first step, an OLS panel regression has been performed on the Swedish hedge funds. For each date, the entire group of 61 Swedish hedge fund returns has been regressed on the different models.

For constant models, the regression is the following:

$$r_{i,t} = \alpha_i + \sum_{k=1}^{K} \beta_k f_{k,t} + \varepsilon_{i,t} \ ,$$

where K is the numbers of factors in each model (CAPM, Fama-French, Fung and Hseih 7-factor model).

For the time-varying models, the following regressions have been performed:

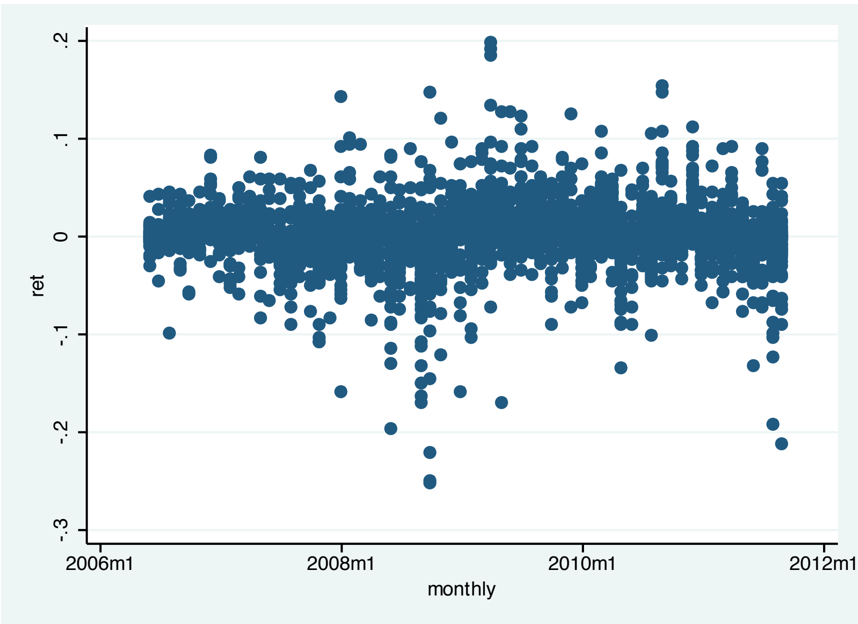
$$r_{i,t} = \alpha_i + \beta_1 f_{1,t} + \beta_2 f_{2,t} + \gamma_1 f_{1,t} Z_{t-1} + \gamma_2 f_{2,t} Z_{t-1}$$
$$+ \delta_1 \sum_{d=1}^{n_t} f_{1,d}^* Z_{d-1}^* + \delta_2 \sum_{d=1}^{n_t} f_{2,d}^* Z_{d-1}^* + \varepsilon_{i,t} \ ,$$

where 1 denotes the market factors and 2 denotes the size-factor.

It is important to point out that in a first stage, regressions are not done on individual funds, as will be done later, but on all hedge fund returns at a given time t. These pooled regressions are equivalent of assuming equal coefficients throughout all funds, and is not intended to test the model's fit (e.g. in terms of R^2); it is merely used to derive coefficients and test the significance of the different parameters.

The data has been controlled for fixed effects, i.e. allowing different alphas for every fund, but there was no evidence for significantly different alphas across funds.

Figure II: Monthly returns of the sample's 61 hedge funds, Jun 2006 to Sep 2011



As can be seen on Figure II, the returns of the 61 hedge funds are largely heterogeneous. Naturally, an attempt to regress all hedge fund returns at once will not yield a high fit in terms of R^2. Further, the crises of 2008 and 2011 additionally brought periods of high volatility and heterogeneity in hedge funds returns, affecting negatively the R^2 of the regressions for hedge funds as a whole.

Table III: Panel regression results of the 61 hedge funds

All Hedge Funds

	CAPM	Fama & French	Fung & Hseih	Time-varying models			
				Z(VIX)	Z(S&P)	Z(TED)	Z(dLevel)
Alpha (p.a.)	1.37%	1.51%	2.12%	1.56%	1.31%	1.39%	1.65%
t-value	*(2.41)***	*(2.71)***	(3.48)**	(2.49)**	(2.06)**	(2.48)**	(3.02)**
OMX	0.16	0.15	0.15	0.16	0.16	0.16	0.15
t-value	*(19.16)***	*(11.25)***	*(16.67)***	*(13.16)***	*(12.10)***	*(11.76)***	*(12.39)***
SMB		0.11	0.13	0.14	0.13	0.12	0.11
t-value		*(8.22)***	*(9.18)***	*(9.81)***	*(9.06)***	*(8.29)***	*(9.75)***
HML		0.02					
t-value		*(0.85)*					
LS Bond			0.01				
t-value			*(1.31)*				
LS Currency			0.00				
t-value			*(-0.51)*				
LS Commodity			0.00				
t-value			*(-0.26)*				
Spread			0.00				
t-value			*(-1.00)*				
Yield			0.01				
t-value			*(1.54)*				
γ(1)				-0.220	-0.357	-0.066	0.102
t-value				(-1.04)	*(-1.12)*	*(-1.89)**	*(2.00)***
γ(2)				-0.292	-0.111	-0.011	0.081
t-value				*(-1.06)*	*(-0.45)*	*(-0.31)*	*(2.07)***
δ(1)				-0.023	0.461	0.041	0.153
t-value				*(-0.12)*	*(1.15)*	*-1.180*	*(0.38)*
δ(2)				0.076	-0.345	0.003	0.163
t-value				*(0.30)*	*(-0.42)*	*(0.09)*	*(0.28)*
Adj. R^2	0.10	0.12	0.12	0.12	0.12	0.12	0.12

* p<0.10; ** p<0.05

Table III shows the results from panel-regression of the 61 hedge funds of all the models, using White robust standard errors. Alphas have been annualised. In the Fung and Hseih regression, "LS" stands for the lookback straddles ABS factors. There are 3436 observations per regression.

As can be seen on Table III, the time-varying models yield a slightly better adjusted R^2 than the CAPM, the Fama-French and the Fund and Hseih 7 variable models. However, as has already been pointed out, a high fit for the models is not expected in these panel regressions. The most important result from these regressions is that that the equity and size factors are highly significant in all the regressions. Moreover, the coefficients revolve around 0.15. From this relatively low but statistically highly significant coefficient, it can be concluded that hedge funds on average are, even if mildly, exposed to the swings in the market, unlike their absolute return strategy would infer.

It can also be noted that the Fung and Hseih 7-factor model's regression yields no significant results for any of the lookback straddles. This can be caused by the fact that they have been constructed on American data and do not fit the Swedish hedge funds returns properly.

A standard method to model hedge fund risk is to use broad-based indices as the basis for analysis (Fung and Hseih (2004)). However, using indices also rests on the assumption that the underlying assets are reasonably homogenous, which is a strong assumption for hedge funds but cannot be worked around.

In the next step, a regression on indices has been performed. The Hedge Fund Average index is used in the regressions presented in Table IV. Sub-indices for each hedge fund style have also been constructed, for which the regression results are presented in the Appendix.

Table IV: Hedge Fund Average Index regression results

	CAPM	Fama & French	Fung & Hseih	Time-varying models			
				Z(VIX)	Z(S&P)	Z(TED)	Z(dLevel)
Alpha (p.a.)	1.23%	1.40%	1.99%	1.50%	1.15%	1.29%	1.53%
t-value	*(1.13)*	*(1.57)*	*(1.57)*	*(1.54)*	*(1.05)*	*(1.48)*	*(1.74)**
OMX	0.15	0.15	0.15	0.16	0.16	0.16	0.15
t-value	*(9.00)***	*(8.91)***	*(8.04)***	*(10.44)***	*(8.76)***	*(11.29)***	*(9.96)***
SMB		0.12	0.13	0.14	0.13	0.12	0.13
t-value		*(4.99)***	*(4.49)***	*(5.48)***	*(5.36)***	*(5.32)***	*(5.82)***
HML		0.01					
t-value		*(0.48)*					
LS Bond			0.01				
t-value			*(1.13)*				
LS Currency			0.00				
t-value			*(-0.08)*				
LS Commodity			0.00				
t-value			*(-0.43)*				
Spread			0.00				
t-value			*(0.77)*				
Yield			-0.16				
t-value			*(-1.22)*				
γ(1)				-0.214	-0.359	-0.065	0.100
t-value				(-1.79)*	*(-0.94)*	*(-2.24)***	*(2.47)***
γ(2)				-0.289	-0.056	-0.011	0.082
t-value				*(-1.28)*	*(-0.16)*	*(-0.59)*	*(2.52)***
δ(1)				-0.006	0.415	0.042	0.163
t-value				*(-0.07)*	*(1.00)*	*(2.25)***	*(0.91)*
δ(2)				0.065	-0.258	0.013	0.174
t-value				*(0.31)*	*(-0.27)*	*(0.34)*	*(0.82)*
Adj. R^2	0.60	0.74	0.72	0.75	0.73	0.75	0.75

* p<0.10; ** p<0.05

p-val total				21.34%	83.59%	11.39%	0.82%
p-val daily				95.19%	58.35%	21.16%	91.95%

Table IV shows the results from the OLS regression of the Hedge Fund Average Index, using White robust standard errors. Alphas have been annualised. In the Fung and Hseih regression, "LS" stands for the lookback straddles ABS factors. There are 64 observations per regression. The last two rows of the table are the p-values for the hypothesis tests (8) and (9).

The adjusted R^2 are much higher for the average hedge fund index than when the regression is performed on all hedge funds at the same time, coming from the fact that

there is only one data point per period. On the other hand, this leads also to far less observations, namely 64, which makes the regression much more sensitive to how many variables are used.
The regressions show relatively high adjusted R^2, ranging from 0.6 for the CAPM model to 0.75 for three of the four conditional models (using VIX, TED spread and dLevel as conditioning variables). Also, there are clear indications that both the equity and the size factors are highly significant in all models, with both coefficients revolving around 0.15, similar to the previous panel regressions.

The CAPM is a relatively reduced model, as it only has one explaining factor, namely the market return. As shown by its comparatively low R^2, it provides a reduced explanation power of the hedge fund returns. As the least interesting regression model in the analysis, it will not receive additional focus in the following sections.

The Fama-French model uses two additional factors over the CAPM, namely the size factor and the high-minus low factor. Not surprisingly, the size factor shows to be highly significant and positive, demonstrating that hedge funds take advantage of the size effect by taking long positions in smaller equities and shorting larger ones. The fact that hedge funds are loosely regulated allows them to relatively freely pursue long-short strategies. In this light, it therefore appears slightly odd that the HML factor shows no sign of significance whatsoever. However, this factor has been derived by Fama and French on American data, and possibly does not reflect the positions that Swedish based hedge funds are taking.

The regression of the Fung and Hseih 7-factor model yields surprisingly deceiving results. As mentioned before, it is indeed the most accepted model when analysing hedge fund returns, and is constructed so as to capture the returns for most hedge fund strategies. In the regression, only the equity and size factors showed to be significant. None of lookback straddles, primarily constructed to capture the strategy from trend-following hedge funds, proved to be significant on the data, maybe coming from the fact that Fung and Hseih computed them on American data. The factors capturing the change in spread and yield, on the other hand, are primarily supposed to capture the strategy of Fixed Income hedge funds. However, the database of returns only counts 7 Fixed Income funds. Moreover, a regression on the Fixed Income index as well as on single fixed income hedge funds proves to be deceiving with very low R^2 as well as significances for all the models' factors.

The time-varying conditional models reveal to have the highest R^2. However, many of the regression coefficients are proven to be not significant. This would imply that there is no typical reaction for the average hedge fund to the change in the conditioning variables. For example, when using the conditioning variable Z = S&P 500 return, there is no clear effect on the sample's risk exposures from an up- or downswing in the conditioning variable. This can come from the fact that the different styles of hedge funds composing the data react differently to such events.

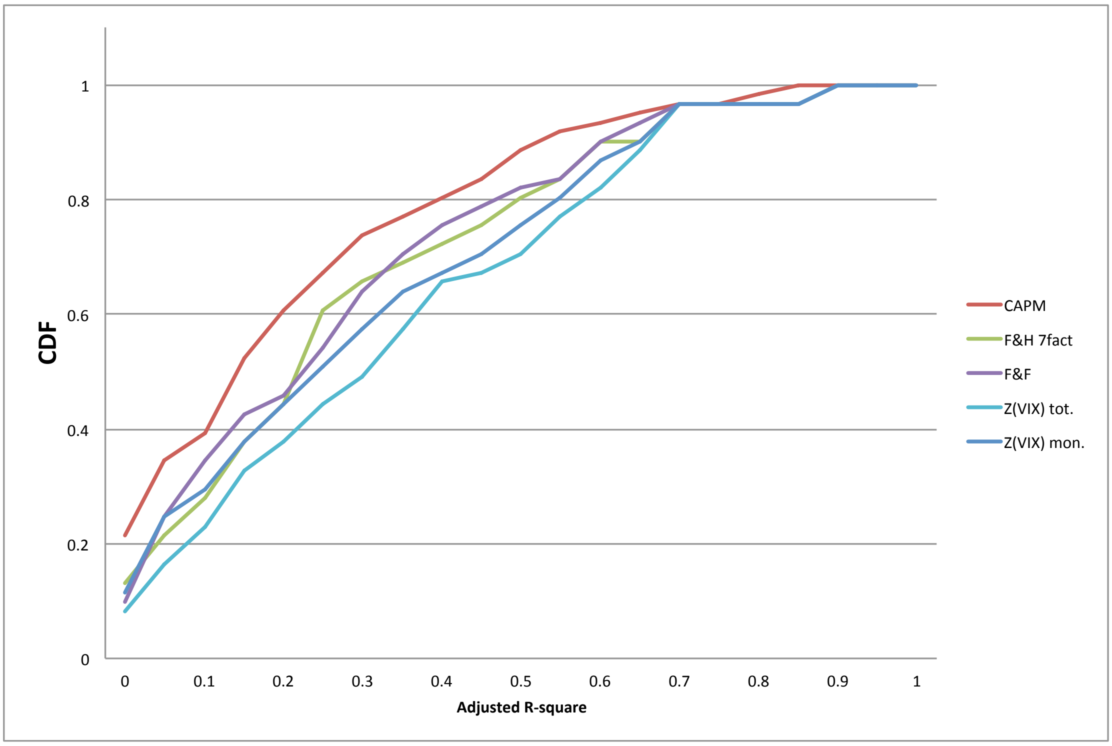
It is to be reminded that the regression parameters γ_1 and γ_2 influence the risk exposure to the factors (i.e. influence the Beta of factor 1 and Beta of factor 2) according to the monthly data of the conditioning variable Z. In the same fashion, the parameters $\delta_1$and δ_2 influence the risk exposure to the factors according to the daily conditioning variable.

To illustrate, we use the regression using dLevel as a conditioning variable. From the regression results, where both γ_1 and γ_2 are significant and positive, we can conclude that an increase in the monthly conditioning variable (i.e. an increase in the Swedish Government's 3-month treasury yield) will increase the risk exposure (i.e. beta) of both the equity factor and the size factor. Thus, assuming a positive return for the two factors at a given time, an increase in the interest rates results in a higher return in the model. The dLevel conditioning variable is the only one rejecting the hypothesis of constant risk exposure on the Average Fund Index, i.e. only for this variable can we see a typical reaction on risk exposure of the average fund. However, better results are obtained when concentrating on different style sub-indices, as can be seen in the Appendix.

Running the regression on every single fund, some interesting facts about the models can be detected. First of all, the distribution of Adjusted R^2 across the funds according to the different models can be analysed. On Figure III, we find that the conditional model using the conditioning variable VIX consistently beats the constant-beta models, as its cumulative distribution function (CDF) lies below everywhere. The lower the CDF line for a model, the better the fit. On Figure III, 60% of the funds have lower adjusted R^2 than 0.4, whereas 80% of the funds in the CAPM regression have a lower adjusted R^2 than 0.4.

Worse results in terms of R^2 are obtained using only data from the monthly conditioning variable (i.e. forcing Delta 1 and Delta 2 to be equal to zero, "Z(VIX) mon." in Figure III) than when applying the entire model ("Z(VIX) tot." in Figure III), which shows the added value of a model capturing daily adjustments in risk exposure.

Figure III: Cumulative distributive function of adjusted R^2 statistics from constant models compared to the VIX conditional model



It can be concluded that the conditional models using both daily and monthly interactions seem to provide higher explanation power of the hedge fund returns than the other static models, including the widely accepted Fung and Hseih 7-factor model.

6.3 Time Variation

On an index basis, a Wald-test with the following null hypothesis can be conducted to test for the significance of time-variation:

$$H_0 : \gamma_i = \delta_i = 0 \qquad \text{vs.} \qquad H_0 : \gamma_i \neq 0 \;\; and \;\; \delta_i \neq 0 \quad (8)$$

A rejection of the null hypothesis indicates that there are signs of significant time-variation in the risk exposure. Failing to reject the null hypothesis however indicates that the time-variation in risk exposure is not significant, in which case the conditional model becomes less relevant.

Whether daily variation in the risk exposures adds value can be analysed by testing that the coefficient of daily interaction is equal to zero:

$$H_0 : \delta_i = 0 \qquad \text{vs.} \qquad H_0 : \delta_i \neq 0 \quad (9)$$

Concerning the average hedge fund index, the significance of the individual conditional coefficients is highly questionable (see Table IV). Indeed, only 5 of the 16 coefficients coming from the 4 different conditioning variables are significant at a 10% confidence, and 4 coefficients are significant at a 5% confidence.

When looking at the hypothesis testing, only the model with dLevel as a conditioning variable rejects the joint hypothesis of constant beta exposure, predominantly coming from the monthly information contained in the conditioning variable (last two rows of Table IV). This result can come from the fact that the 61 hedge funds included in the broad index are not a homogeneous group, and are exposed to the different conditioning variables in different ways. Indeed, when running the regressions on the different hedge fund styles, different results are perceived (regression results are reported in the Appendix).

Not surprisingly, the equity hedge fund index (the average of the equity hedge funds' returns) yields the best result from the regression, explained by the fact that two factors in the model are equity-related. Adjusted R^2 for the conditional models ranges from 0.76 to 0.80, and 12 out of 16 possible coefficients for time-variation are significant at a 10% confidence (8 are significant at a 5% confidence). Moreover, both the hypotheses (8) and (9) are rejected at a 5% confidence for all conditioning variables. These are strong indications arguing for the existence of time-variation of the risk exposures, and both monthly and daily information contained in the conditional variables is of value.

It is worth mentioning that the models show very poor results for the Fixed Income index, with no evidence for time-variation in beta and adjusted R^2 close to zero. This poor performance can be the result of using two equity-related factors in the models, which is not optimal when evaluating a fixed income strategy. Moreover, the models perform poorly on an individual fund level for all the 7 Fixed Income hedge funds.

There is strong evidence of time-variation in the regression on the funds-of-fund index, as both the hypotheses are rejected for the 4 different conditioning variables. An explanation for these good results could be that funds-of-funds capture a large spectrum of hedge funds, providing a good picture of the industry. Moreover, the approach of using public information as conditioning variables capture systematic trends and can be particularly accurate when analysing, diversified and rather homogeneous portfolios (as fund-of-funds) .

Finally, the multi-strategy and managed futures indices yield mixed results. Whereas there is evidence of overall time-variation for most of the conditional variables, neither of the indices shows evidence of daily variation in risk exposure on an index level.

After having looked at evidence of time-variation in risk exposure at the index level, the tests have also been conducted on a single fund basis. The proportion of the 61 funds that show evidence of time-variation on a joint daily and monthly basis as well as on a monthly basis only are reported in Table V.

Table V: Proportion of funds showing significant time-variation:

Category	VIX		S&P		TED		dLevel		Average		Nb of funds
	Total	Monthly	Total	Monthly	Total	Monthly	Total	Monthly	Total	Monthly	
Equity	57.1%	28.6%	66.7%	42.9%	42.9%	38.1%	57.1%	47.6%	54.8%	39.3%	21
Fixed Income	71.4%	57.1%	57.1%	0.0%	42.9%	14.3%	42.9%	28.6%	35.7%	25.0%	7
FoF	66.7%	46.7%	66.7%	13.3%	53.3%	46.7%	46.7%	46.7%	61.7%	38.3%	15
Multi-Strategy	85.7%	28.6%	71.4%	14.3%	42.9%	28.6%	57.1%	28.6%	64.3%	25.0%	7
Managed Futures	45.5%	9.1%	72.7%	0.0%	27.3%	9.1%	27.3%	27.3%	45.5%	11.4%	11
ALL	62.3%	32.8%	67.2%	19.7%	42.6%	31.1%	47.5%	39.3%	53.7%	30.7%	61
Significance	***5%***										

Table V reports the proportion of funds in each category that shows significant time-variation in risk exposure using the different conditioning variables. The column "Total" shows the proportion of funds rejecting constant risk exposure hypothesis (8). The column "Monthly" shows the proportion of funds rejecting the null hypothesis of constant risk exposure using only the monthly interaction term (similar to the Ferson-Schadt (1996) procedure, by forcing the gamma coefficients to be equal to zero). The column "Average" is a simple arithmetic average of the proportions across the four conditioning variables.

Table V shows that a high proportion of funds recognise significant of time-variation on a single fund basis.

Even though the individual conditioning parameters may not be all statistically significant on a fund level regression, they are jointly significant for 65.6% of the funds using VIX as a conditioning variable. At a 5% confidence, we expect 5% of rejections if the nulls were true. When analysing whether 62.3% is significantly different from 5% given the sample size, we find that the critical value for rejecting the null hypothesis of zero-parameters is 10.5%. Using monthly and daily conditioning data, a higher proportion of rejection than the critical value is found for all conditioning variables and hedge fund styles.

Further, it is found that daily data is valuable by comparing the higher proportion of funds rejecting constant risk exposure when using daily and monthly conditioning variables instead of monthly only. On average, the daily information contained in the conditioning variable helps identify time-variation in 53.7% of the funds instead of 30.7% using monthly information only. This is consistent with hedge funds updating their positions with high frequency that monthly conditioning variables cannot capture. Further, it can be noticed that the daily information is more valuable using conditioning variables that tend to be updated on a higher frequency (espescially S&P 500) than more "tempered" conditioning variables (dLevel).

When comparing the different hedge fund styles, it can be noticed, as in Patton and Ramadorai (2011) that multi-strategy and fund-of-funds show the highest proportions of funds showing significant time-variation in risk exposure. As Patton and Ramadorai (2011) conclude, there are two main explanations. First of all, their returns are essentially an average of multiple funds/strategies, making them less noisy. Second, the broad conditioning variables capture systematic trends, rather than fund-specific reasons for shifts in risk exposure, and are morel likely to be pertinent on larger and more diversified portfolios.

6.4 Alpha

Using the regressions on individual funds, the average alpha according to the models is computed.

The proportion of funds reporting significant alpha is roughly 25% for both the constant and time-varying models. In the static model, when γ and δ are set to zero, the average annualised fund alpha is 1.25%, while it reaches a slightly higher value of 1.44% when using the conditional models, a difference of 19 bps.

When concentrating on funds that can reject constant risk exposure, difference in alpha delivered by the models is even greater. The static model yields an average alpha of 1.23% while it averages 1.54% for the conditional models, a difference of 31 bps.

As in Patton and Ramadorai (2011) and Ferson and Schadt (1996), these different results are an indication, even if weak, that the constant risk exposure model underestimates the ability of hedge funds to deliver alpha, by omitting that public information that is correlated with their risk exposures. It indicates that using a time-varying model for performance assessment is beneficial for fund managers, as it recognises a better ability for generating abnormal returns.

The performance of some funds may improve while declining for others when using the conditional model instead of the static model, which is not captured by simply comparing the average alpha. The absolute value of the difference in alpha for all funds using the two types of models has been measured, resulting in a rather large difference of 1.25% (around the same size as the static alpha).

Finally, the use of the two different types of models did not seem to have a large impact on performance rankings. The ranking correlation of alphas using constant and time-varying risk exposure is 88%.

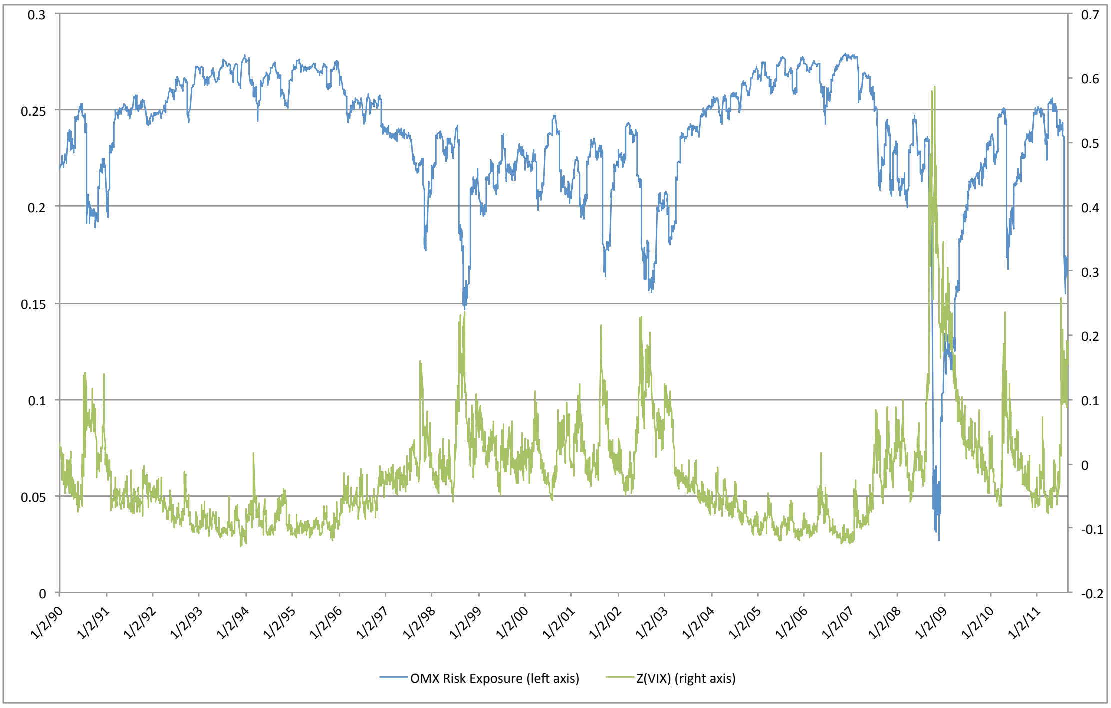
6.5 Evolution of Beta in Conditional Models

Using the regression results, the risk-exposure of hedge funds to the model's factors has been computed on a daily basis according to formula (4).

$$\beta_{i,1,d} = \beta_{i,1} + \gamma_{i,1} Z_{d-1} + \delta_{i,1} Z^*_{d-1}$$
$$\beta_{i,2,d} = \beta_{i,2} + \gamma_{i,2} Z_{d-1} + \delta_{i,2} Z^*_{d-1}$$

A whole range of time-varying betas depending on the regressed variable (individual fund, style index or fund average index) and on the conditioning variable are obtained. The following graph depicts the evolution of the risk exposure to the market (OMX 30) of the equity hedge fund index using the conditioning variable VIX.

Figure IV: Time-varying risk exposure of the Equity index to the market factor



The regression period is June 2006 to September 2011. The coefficients from that regression have been used together with historic data of the parameters to estimate the risk exposure to the market starting in February 1990.

As expected, in times of high volatility, when the conditioning variable for VIX is high, the risk-exposure to the market factor decreases. As volatility on the S&P 500 increases and financial markets around the world become more nervous, often in bad times, hedge fund managers tend to cut their exposure to the equity factor. During the Lehman Brothers crisis, the VIX conditioned exposure to the OMX reaches its all time low at ¼ of its average value in November 2008, reaching normal levels only around July 2009. Conversely, in times of low volatility, hedge fund managers will increase their exposure to the stock market to participate in a likely upswing of returns.

When comparing the risk exposure to the 2 factors using different conditioning variables, substantial differences appear. The correlation of the betas on the respective factors stays in the ranges from -0.3 to 0.2. This tells us that the conditioning variables contain different and sometimes contradictory information concerning the risk exposures of the hedge funds. While this result does not invalidate the choice of conditioning variables (a very high correlation would imply redundancy in the choice of conditioning variables), it also reveals the limitations of our method's ability to estimate true risk exposure. Indeed, using more than one conditioning variable at the same time would undermine the regression, an effect of the "curse of dimensionality", as too many variables would be used with limited historic data (the addition of one conditioning variable brings 8 new parameters to the regression). However, as there is different information in the conditioning variables, return estimations render different outcomes. The choice of the best conditioning variable for an event study type of return estimation (during a reduced period, or a particular crisis) has therefore to be argued by a logical and practical analysis.

Table VI: Correlations of the conditional models' risk exposure to the equity factor

Correlation	B1(VIX)	B1(S&P)	B1(TED)	B1(dLevel)
B1(VIX)				
B1(S&P)	-0.30			
B1(TED)	0.22	-0.07		
B1(dLevel)	0.06	-0.03	0.10	

Table VII: Correlations of the conditional models' risk exposure to the SMB factor

Correlation	B2(VIX)	B2(S&P)	B2(TED)	B2(dLevel)
B2(VIX)				
B2(S&P)	-0.07			
B2(TED)	0.21	-0.06		
B2(dLevel)	0.12	-0.01	-0.03	

6.6 Comparison of Monthly and Daily Data

Out of the 61 hedge funds, 9 funds have reported daily returns to a Handelsbanken database. The following regressions has been run on the daily data:

$$r_{i,d} = \alpha_i + \beta_{i,1} f_{1,d}^* + \beta_{i,2} f_{2,d}^* + \gamma_{i,1} f_{1,d}^* Z_{d-1} + \gamma_{i,2} f_{2,d}^* Z_{d-1} + \delta_{i,1} f_{1,d}^* Z_{d-1}^* + \delta_{i,2} f_{2,d}^* Z_{d-1}^* + \varepsilon_{it} ,$$

where α_i is the daily alpha of fund i, $\beta_{1,i}$ and $\beta_{2,i}$ are the constant exposure to the two factors, $\gamma_{i,1}$ and $\gamma_{i,2}$ capture variations in risk exposure that occur at the monthly frequency (within variable Z_t) and $\delta_{i,1}$ and $\delta_{i,2}$ capture variations at the daily frequency (within variable Z_d^*).

The coefficients derived from the daily and the monthly data are used to derive the risk exposures on respectively daily and monthly returns.

Table VIII: Correlation of risk exposures from monthly and daily returns using VIX as a conditioning variable

Fund Name	Corr. Beta 1	Corr. Beta 2
Catella Hedgefond	0.74	-0.38
Catella Europa Hedge	1.00	0.87
Atlant Stability	0.77	0.83
Skandia Global Hedge	0.96	-0.28
Tanglin	0.87	-0.87
Evli Makrohedgefond	-0.41	-0.41
Scientia Hedge	0.99	-0.60
P&N Yield	0.95	0.99
P&N Idea	-0.68	0.94

From the Table VIII, several interesting conclusions can be drawn. For the fund Catella Europa Hedge, for example, there is a high correlation between the betas for both factors using daily and monthly returns. Even though the regression coefficients are not identical, they are in the same ballpark, and of the same sign. It results in similar time-varying betas using daily and monthly return and a high correlation.

Interestingly, the funds that show significant time-varying risk exposure tend to have the highest correlation between betas from monthly and daily data. Similarly, the funds showing negative or no correlation (e.g. Evli Makrohedge, with insignificant time-variation on neither monthly or daily return data) have almost exclusively low or no significant time-varying risk exposures.

These results indicate that it is possible to obtain reliable estimates of daily risk exposure using monthly data for funds showing significant time-variation. Of course, the limited sample of funds for which this test is performed does not constitute any proof. Moreover, comparisons on a single fund basis are not ideal, as any noise in the data can invalidate the regressions. There would be a stronger case by applying this reasoning to a larger hedge fund index for which both daily and monthly returns are available.

6.7 Return Estimation

Hedge funds are relatively new on the Swedish market. Their short existence renders difficult the task of evaluating their true long-term performance, and their resistance to bearish times. Moreover, hedge funds have a large freedom in undertaking investments without sharing their strategies. The opaqueness of their operations and the lack of performance reporting standard render their benefits hard to evaluate for investors. To take advantage of the insights from the time-varying model, daily return estimations have been performed for all hedge funds during the period 1990 to 2006. The returns have been computed the following way using the coefficients from the precedent regressions:

$$\hat{R}^*_{i,d} = r^*_{f,d} + \hat{\alpha}_i/n_t + \hat{\beta}_{i,1}f^*_1 + \hat{\beta}_{i,2}\, f^*_2 + \hat{\gamma}_{i,1}f^*_{d,1}Z_{d-1} + \hat{\gamma}_{i,2}f^*_{d,2}Z_{d-1} + \hat{\delta}_{i,1}f^*_{OMX}Z^*_{d-1} + \hat{\delta}_{i,2}f^*_{SMB}Z^*_{d-1}\,, \qquad (10)$$

which, by combination with equation (4), is equivalent to:

$$\hat{R}^*_{i,d} = r^*_{f,d} + \hat{\alpha}_i/n_t + \hat{\beta}_{i,1,d}f^*_{OMX} + \hat{\beta}_{i,2,d}f^*_2 \quad . \qquad (11)$$

$\hat{R}^*_{id}$ is the estimated daily total return of the fund *i* on day *d*, and $r^*_{f,d}$ is the risk free rate on day *d*.

It is important to notice that the regressions have been run on the period June 2006 to September 2011. The computed parameters have then been applied to the previous estimation period's data of the parameters, resulting in hypothetical daily returns for Swedish hedge funds. While this approach gives a time-variation of the exposure to the model factors, it also implies that the reaction to changes to the conditional variable are constant, as the β_i, γ_i and δ_i coefficient are fixed values. This is a limitation to the model as it is likely that the degree to which hedge fund managers shift their exposure to model factors in different conditions is not identical, and certainly depends on the intensity of the events. However, this model possesses an advantage over an unconditional model where the risk exposure of hedge funds in itself is kept constant over the period.

Another disadvantage of the model in performing return estimation is its heavy reliance on two factors, the OMX 30 return and the size spread return. The estimation of returns for a given fund will therefore solely come from a combination of these two factors (weighted by their respective time-varying beta), the risk free rate and the fund's alpha according to the model.

A database of all the 61 hedge funds' estimated returns during the period February 1990 to May 2005 has been constructed. Table IX delivers some statistics from the estimated returns of the 61 funds, with VIX as a conditional variable. All conditioning variables yield similar results for the average compounded returns.

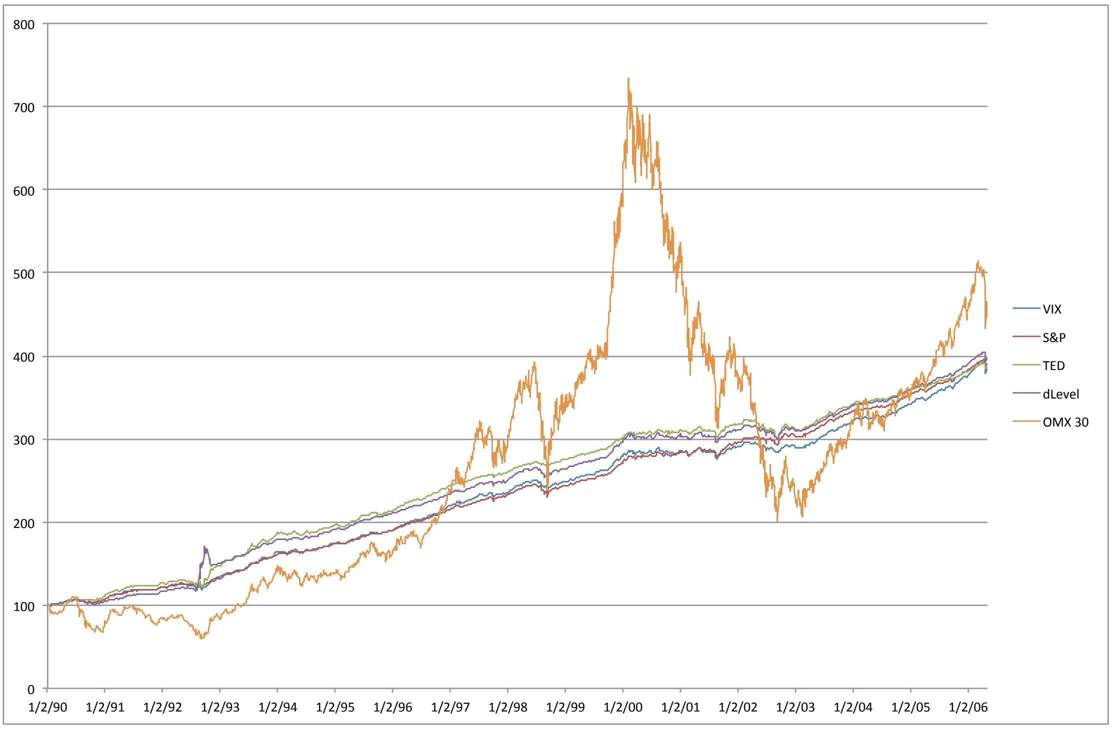
Table IX: Estimated annual returns and performance measures using VIX (Feb 1990-May 2006)

Category	Q1 Funds Returns	Avg. Return	Q3 Funds Returns	Avg. St. Dev.	Avg. Sharpe	5% VaR	Nb of Funds
Equity	6.9%	9.1%	11.7%	7.7%	0.41	3.0%	21
Fixed Income	5.3%	7.6%	8.7%	2.4%	0.65	0.4%	7
FoF	6.3%	7.8%	8.4%	3.1%	0.57	0.8%	15
Multi	4.0%	6.5%	9.2%	5.7%	0.09	2.3%	7
Managed Futures	6.9%	9.4%	12.4%	6.6%	0.52	2.5%	11
ALL	5.4%	8.4%	10.7%	5.5%	0.43	2.0%	61
OMX 30	n.a.	9.6%	n.a.	24.2%	0.15	11.0%	n.a.

Table IX shows attractive return characteristics for hedge funds compared to the equity index, as they offer substantially less volatility and VaR. The average hedge fund delivers a Sharpe ratio almost three times larger than the OMX 30.

The different hedge funds' returns are not captured perfectly by the models (as the generally low R^2 shows on individual funds), so the out of sample estimation of a single funds' returns have a limited reliability. We will therefore focus on the Hedge Fund average index. Four different projections have been performed, stemming from the four different conditioning variables. Figure V shows a stable evolution Hedge Fund average Index compared to the OMX 30.

Figure V: Daily evolution of the estimated Hedge Fund Average Index (using the four different conditioning variable) and the OMX 30, Feb 1990 to May 2006



Let us focus on two different events of distress during the estimation period, namely the Swedish banking and currency crisis of 1991-1992, and the Russian default and LTCM collapse in 1998.

6.7.1 Swedish Banking and Currency Crisis

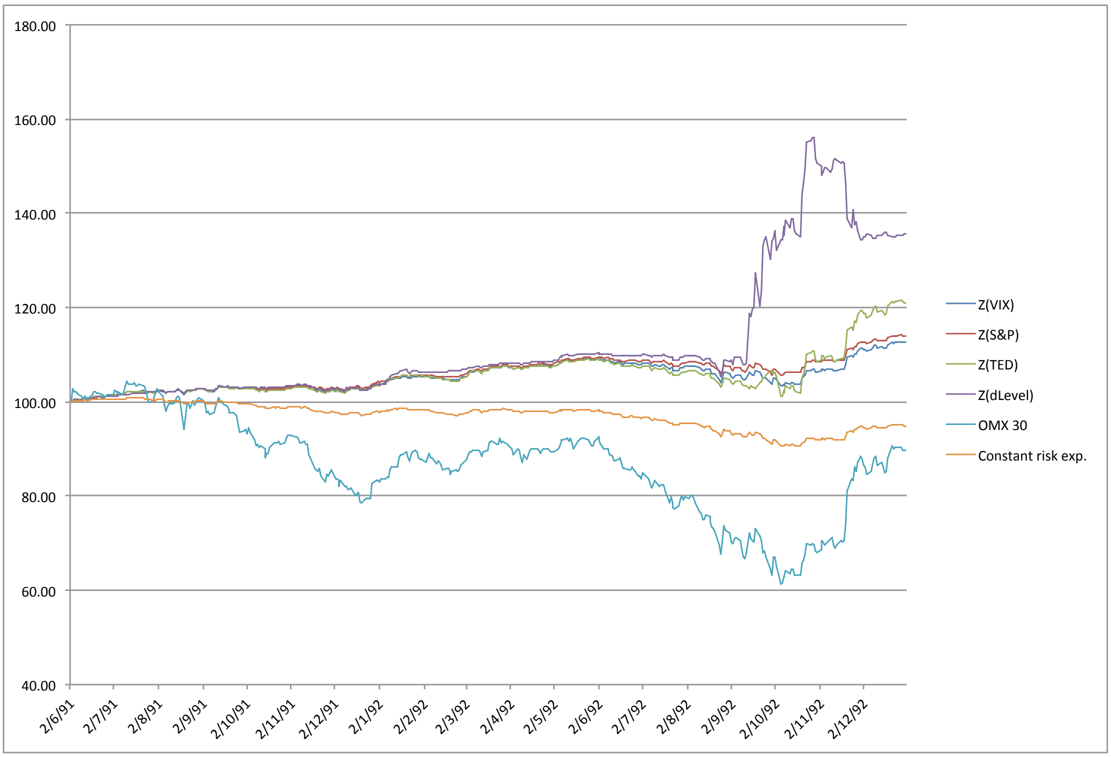
The Swedish banking crisis is one of the country's most severe post World War II economic downturn. The Swedish government had long focused on full-employment at the expense of inflation at the expense of a substantial role of government in the economy. In 1985, lending was fully liberalised which led to a credit boom, clearly reflected by soaring real estate prices. Consumption was also boosted, and the Swedish Central Bank (Riksbanken) could not mitigate the boom with using monetary policy, as the currency was pegged to a basket of currencies. In 1990, the already high domestic interest rates were further pushed up by the reunification of Germany. Asset price deflation was inevitable, which had a profound impact on financial markets and balance sheets. Speculative attacks during 1989-1992 on the currency forced the Riksbanken to raise nominal interest rates in order to keep the peg, which accelerated the real estate bust. In September 1992, the overnight rate attained 500%. The krona was finally set to float freely in November 1992 (Jonung (2009)).

From 1990 to 1992, the OMX index lost 14%, reaching a low for the period in October 1992.

The four conditioning variables were used to estimate the returns of the hedge fund average index during that period. Of these four variables, only 2 will be directly impacted by the increase in the government bonds, namely TED and dLevel. In this context, the other two conditioning variables (VIX and S&P) do not reflect the situation on the Swedish market, as this was a domestic crisis.

From the regression of the fund average index using the conditioning variable dLevel (see Table IV), it can be noticed that all the coefficients are positive, implying that all other things equal, an increase in the interest rate brings a greater risk exposure towards the two factors. This result seems to be counter-intuitive, as a greater interest rate would logically give the incentive to move assets away from the stock market to invest in bonds, and conversely. However, this effect is one of the limitations of regression-based models for out-of-sample assessment. The estimation period is June 2006 to September 2011, times during which yields on government bonds have been pushed down to extremely low levels due to the turbulent economic environment. At such low levels, their effect on risk exposure of hedge funds can be misleading when applying to completely different settings.

Figure VI: Return estimation of the average hedge fund index, early 90's:



From Figure VI, a significant difference in the estimation of the average hedge fund return depending on the conditioning variable can be seen starting September 1992. The government raised interest rates to extreme levels in order to keep the peg of the Swedish currency, resulting in a 3-month government bond reaching up to 35%. Those extreme conditions have a large effect on the models using the conditioning variables TED and dLevel, resulting in large shifts in risk exposure.

The return estimation using dLevel seems however somewhat unrealistic: the predicted hedge fund average index gains over 40% in the two-months period starting in September 1992. It is unlikely that hedge fund managers would have time to react that fast and permanently to the increase in the 3-month government. From a risk perspective, using the dLevel conditioning variable, 6 of the 61 hedge yield returns inferior to 100% during a single day during the week of September 14th 1992, and 7 additional funds lose more than 90% of their June 1991 value by December 1992. However, the estimated returns of the remaining funds are so large that the hedge fund average returns largely positive results.

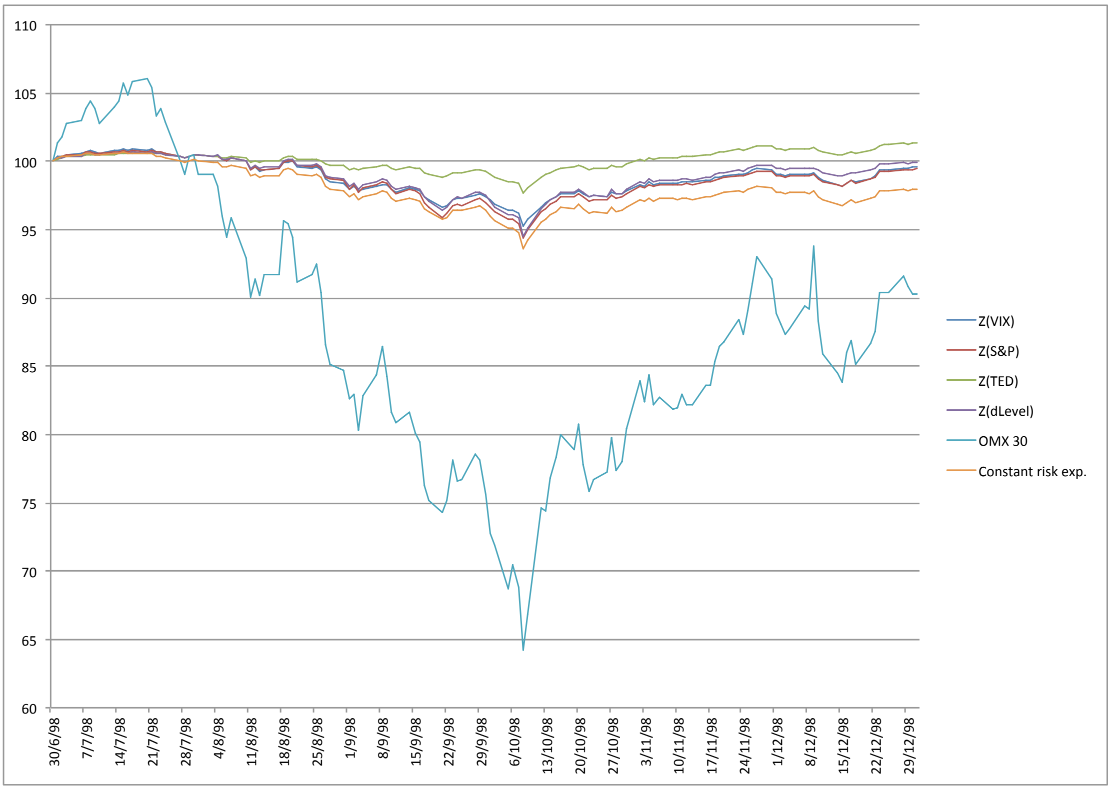
The estimations using the other conditioning variables are approximately in-line with each other. The estimation using the TED variable shows a certain reaction to the shock in interest rates, but its result estimation does not widely differ from the VIX and S7P conditional models.

The return estimations of the conditional models can be compared to the constant risk exposures model (where both γ and δ are forced to be zero). The estimation shows better return results for hedge funds when allowing for time-variation. The return difference shows the benefits for fund managers of active management based on the public information in comparison to passive management.

6.7.2 Second half of 1998

In August 1998, Russia devaluated the ruble and defaulted on its debt, due to both exogenous factors (Asian crisis of 1997, decreasing oil prices) and a dramatic domestic economic situation. Shortly after, financial markets globally plummeted. The largest hedge fund at the time, Long Term Capital Management (LTCM) started to have serious liquidity issues because of extreme leverage and had to exit unfavourable positions until it was bailed out by the Federal Reserve in September 1998. In Sweden, the OMX 30 lost about 40% from July 1998 to October 1998, but recovered relatively fast.

Figure VII: Return estimation of the average hedge fund index in H2 1998:



The estimations of the average hedge fund return during that period remain rather flat. This is the result of a decreased exposure to the equity index, particularly when using TED as a conditioning variable. Again, it appears beneficial for fund managers to shift their risk exposures, as can be seen by comparing the time-varying models' returns to the constant risk exposure returns.

The effect of this crisis would probably have been much deeper for Swedish hedge funds, as they would have likely been exposed both to the Russian default and the LTCM collapse much more than the models can tell. However, as this cannot be captured by the conditioning variables, the estimations yield very stable returns.

The results from the two downturns of the 1990's show the limitations of the models when it comes to out-of-sample return estimation. The daily information helps analysing the dynamic risk exposure to the factors and its effect on the returns. However, the rigidity of the model can be particularly observed during the estimations around the Swedish banking crisis, as the reaction to a large disturbance in the conditional variables remains constant, unaffected by the importance of the event. The estimation during the second half of 1998 stresses the fact that the conditioning variables are not exhaustive and do not capture periods of extreme stress on the financial markets.

7. Conclusions

Recent studies have underlined the importance of taking into account the dynamic nature of hedge fund risk exposures, not the least for performance evaluation. The work of Ferson and Schadt (1996) using public information as conditioning variables has been followed to introduce time-varying risk exposures, and an even higher frequency model as put forward by Patton and Ramadorai (2011) has been applied. Such time-varying model performs well on statistical grounds when applied to Swedish hedge funds, even better than other commonly accepted models in hedge fund research. By using daily return data of hedge funds, there were good grounds to support the methodology of using monthly data to successfully derive daily shifts in risk exposure. Strong evidence of time-variation in risk exposure has been found for more than half of the sample's hedge funds. The daily information contained in the model's conditioning variables reveals to be valuable, which is consistent with the fact that hedge funds update their positions at high frequency.

As a conclusion, taking into account the dynamic nature of hedge funds' trading, which is at the heart of their strategy, is an essential part of performance evaluation. Although the model presented in this study is of a rather simple nature, time-varying models present advantages over more established constant models and should be given more consideration in future research.

References

Agarwal, V. and N. Y. Naik, 2004, Risks and Portfolio Decisions Involving Hedge Funds, *Review of Financial Studies*, 17(1), 63-98.

Aragon, G., 2005, Share restrictions and asset pricing: Evidence from the hedge fund industry, *Journal of Financial Economics* 83, 33-58.

Asness, C.; R. Krail; and J. Liewi, 2002, Do Hedge Funds Hedge? *AQR Capital Management, LLC*, 3-4.

Banz, R, 1981, The Relationship between Return and Market Value of Common Stocks, *Journal of Financial Economics*, 9, 3-18.

Black, F, Jensen, M, and Scholes, M, 1972, The Capital Asset Pricing Model: Some Empirical Findings, in Jensen, M (Eds) *Studies in the Theory of Capital Markets, Praeger*, New York, 79-124.

Boyson, N, Stahel, C, and Stulz, R, 2010, Hedge Fund Contagion and Liquidity Shocks, *Journal of Finance*, 65 (5), 1789–1816.

Brooks, C., and Kat, H. 2002, The statistical properties of hedge fund index returns and their implications for investors, *The Journal of Alternative Investments*, 5, 26–44.

Brown, S.J., W. Goetzmann, and R. Ibbotson. 1999, Offshore Hedge Funds: Survival & Performance, 1989–95, *Journal of Business*, vol. 72, no. 1 (January):91–118.

Edwards, F. R., 1999, Hedge funds and the collapse of Long-Term Capital Management, *The Journal of Economic Perspectives*, Vol. 13, no. 2, spring.

Fama, E, and French, K, 1992, The cross-section of expected stock returns, *Journal of Finance*, 47 (2), 427-465.

Fama, E, and French, K, 1993, Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics*, 33, 3-56.

Ferson, W.E. and R.W. Schadt, 1996, Measuring Fund Strategy and Performance in Changing Economic Conditions, *Journal of Finance*, 51, 425-461.

Fung, W., and D.A. Hsieh, 1997, Empirical characteristics of dynamic trading strategies: the case of hedge funds, *Review of Financial Studies,* 10, 275-302.

Fung, W., and D.A. Hsieh, 2001, The risk in hedge fund strategies: theory and evidence from trend followers, *Review of Financial Studies,* 14, 313-341.

Fung, W., and D.A. Hsieh, 2002a, Hedge Fund Benchmarks: Information Content and Biases, *Financial Analysts Journal,* 58(1), 22-34.

Fung, W. and Hsieh, D. A. 2002b, Asset-based styles factors for hedge funds, *Financial Analysts Journal,* 58(5), 16-27.

Fung, W., and D.A. Hsieh, 2004a, Hedge fund benchmarks: A risk based approach, *Financial Analysts Journal,* 60, 65-80.

Fung, W., and D.A. Hsieh, 2004b, Asset-Based Style Factors for Hedge Funds, *Financial Analysts Journal*, 60, 65-80.

Fung, W., D.A. Hsieh, N.Y. Naik and T. Ramadorai, 2008, Hedge funds: Performance, Risk and Capital Formation, *Journal of Finance*, 63(4), 1777-1803.

Fung, W., and D.A. Hsieh, 2009, Measurement Biases in Hedge Fund Performance Data: An Update, *Financial Analysts Journal,* 65(3), 36-38.

Hasanhodzic, J., A. W. Lo. 2007. Can hedge-fund returns be replicated?: The linear case, *Journal of Investment Management,* 5(2) 5–45.

Joenväärä, J, Kosowski, R and Tolonen, P, 2012, Revisiting 'Stylized Facts' About Hedge Funds, Working Paper (January 20, 2012).

Koh, Francis, Lee, David K.C. and Phoon, Kok Fai 2002, Investing in Hedge Funds: Risks, Returns and Pit- falls, Ferrell Focus Working Paper.

Lintner, J, 1965, The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets, *Review of Economics and Statistics*, 47, 13-37.

Patton, A. and Ramadorai, T. 2011, On the High-Frequency Dynamics of Hedge Fund Risk Exposures. CEPR Discussion Paper no. 8479. London, Centre for Economic Policy Research.

Rosenberg, B, Reid, K and Lanstein, R, 1985, Persuasive Evidence of Market Inefficiency, *Journal of Portfolio Management*, 11, 9-17.

Sadka, R., 2009, Liquidity Risk and the Cross-Section of Expected Hedge Fund Returns, forthcoming in *Journal of Financial Economics*.

Sharpe, W, 1964, Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk, *Journal of Finance*, 19, 425-442.

Stattman, D, 1980, Book Values and Stock Returns, *The Chicago MBA: A Journal of Selected Papers,* 4, 25-45.

Non-Academic Sources

CPI Financial, 2012, Hedge fund industry sees most new launches since 2007, *CPI Financial,* March 13, 2012

Fieldhouse, S, 2008, Hedge Fund Replication: A Revolution In The Making?, *The Hedge Fund Journal,* June 1, 2008.

Jones, S, 2012, Hedge fund industry fights back on criticism, *Financial Times*, April 24, 2012

Jonung, L, 2009, The Swedish Model for Resolving the Banking Crisis of 1991-1993. Seven Reasons Why it Was Successful*, European Commission Economic Papers*, 360.

Mirsky, R, Cowell, A, Baker, A, 2012, The value of the hedge fund industry to investors, markets, and the broader economy, *KPMG and AIMA,* by the Centre for Hedge Fund Research Imperial College, London

Textbooks

Bodie, Z, Kane, A, Marcus, A, 2008, "Investments", seventh international edition, McGraw-Hill.

Electronic resources

David A. Hsieh's Data Library: Hedge Fund Risk Factors
http://faculty.fuqua.duke.edu/~dah7/HFRFData.htm

Datastream
Used to obtain market data

Finansinspektionen, Specialfondernas Riskmått, June 2006 to December 2011.
http://www.fi.se/Marknadsinformation/Fondinnehav/Specialfondernas-riskmatt/?Year=2011

Fondbolagens Förening, Fondförmögenhet.
http://www.fondbolagen.se/sv/Statistik--index/Fondformogenhet/

Handelsbanken
Daily hedge fund returns
http://web.msse.se/shb/sv/history

Kenneth R. French - Data Library
http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Morningstar
Used in the hedge fund selection process
http://www.morningstar.se/

8. Appendix

List of Included Funds

	Fund Name	Fund Manager	Fund Style
1	Adrigo Hedge	A-Brokers AB	Equity
2	Aktie-Ansvar Graal	Aktie-Ansvar AB	Equity
3	Alcur	Consafe Capital Advisors AB	Equity
4	Atlant Explora	Atlant Fonder AB	Equity
5	Atlant Sharp	Atlant Fonder AB	Equity
6	Atlant Stability	Atlant Fonder AB	Equity
7	Brummer Archipel	Archipel Asset Management AB	Equity
8	Brummer Futuris	Futuris Asset Management AB	Equity
9	Brummer Zenit	Zenit Asset Management AB	Equity
10	Catella Europa Hedge	Catella Fondförvaltning AB	Equity
11	Catella Hedgefond	Catella Fondförvaltning AB	Equity
12	Cliens Absolut Aktier Sverige	Amrego Kapitalförvaltning AB	Equity
13	Consepio	Wiborg Kapitalförvaltning AB	Equity
14	Handelsbanken Europa Hedge Selektiv	Handelsbanken Fonder AB	Equity
15	Lannebo Alpha	Lannebo Fonder AB	Equity
16	Max Mitteregger Gladiator	Max Mitteregger Kapitalförvaltning AB	Equity
17	QQM Equity Hedge	Navitor Kapitalförvaltning AB	Equity
18	Remium 1	Remium Aktiv Förvaltning AB	Equity
19	Simplicity Neutral	Simplicity AB	Equity
20	Systematiska Risk-Reward	Systematiska Fonder JPA AB	Equity
21	Zaramant Healthcare Fund	Zaramant Fonder AB	Equity
22	ALFA Energy Fund	Nordic Commodity Funds AB	Fixed Income
23	Brummer Nektar	Nektar Asset Management AB	Fixed Income
24	Carlsson Noren Macro Fund	Carlsson Norén Asset Management AB	Fixed Income
25	Excalibur	Excalibur Värdepappersfond AB	Fixed Income
26	Handelsbanken Fixed Income Absolute Return	Handelsbanken Fonder AB	Fixed Income
27	Healthinvest Global L/S	Healthinvest Partners AB	Fixed Income
28	SEB Hedge Fixed Income	SEB Investment Management AB	Fixed Income
29	Agenta Hedge	Agenta Investment Management AB	FoF
30	DnB NOR Prisma	DnB NOR Asset Management AB	FoF
31	Ekvator Absolut	Coeli AB	FoF
32	Ekvator Trygghet	Coeli AB	FoF
33	Guide Multihedge	Whitebeam Fonder AB	FoF
34	Indecap Guide Hedgefond 2	Indecap AB	FoF
35	Merrant Select	Merrant Fonder AB	FoF
36	Multifond Strategi	Moderna Fonder & Analys AB	FoF
37	Nordea All Hedge Fund	Nordea Fonder Aktiebolag	FoF
38	OPM Alfa SEK	Optimized Portfolio Management Stockholm	FoF
39	OPM Global Hedge	Optimized Portfolio Management Stockholm	FoF
40	OPM Vega	Optimized Portfolio Management Stockholm	FoF
41	Robur Access Hedge	Swedbank Robur Fonder AB	FoF
42	SEB Multihedge	SEB Investment Management AB	FoF
43	Skandia Global Hedge	Skandia Fonder AB	FoF
44	Ability Hedge	Ability Asset Management Scandinavia	Managed Futures
45	Atlant Edge	Atlant Fonder AB	Managed Futures
46	Brummer Manticore	Manticore Capital AB	Managed Futures
47	Coeli Spektrum	Coeli AB	Managed Futures
48	eTurn AktieTrend	Eturn Capital Management AB	Managed Futures
49	Lynx	Lynx Asset Management AB	Managed Futures
50	P&N Idea	Prior & Nilsson Fond- och	Managed Futures
51	P&N Yield	Prior & Nilsson Fond- och	Managed Futures
52	Shepherd Energy Fund	Shepherd Energy AB	Managed Futures
53	Stella Nova	Stella Asset Management AB	Managed Futures
54	Systematiska AMDT HEDGE	Systematiska Fonder JPA AB	Managed Futures
55	Brummer Multi-Strategy	Brummer Multi-Strategy AB	Multi-Strategy
56	Evli Hedge	Evli Fonder Aktiebolag	Multi-Strategy
57	Evli Makrohedgefond	Evli Fonder Aktiebolag	Multi-Strategy
58	RAM ONE	RAM One AB	Multi-Strategy
59	Scientia Hedge	Scientia Fund Management AB	Multi-Strategy
60	Systematiska Bas	Systematiska Fonder JPA AB	Multi-Strategy
61	Tanglin	Tanglin Asset Management AB	Multi-Strategy

Regression results, style indices

Equity Index

	CAPM	Fama & French	Fung & Hseih	Time-varying models			
				Z(VIX)	Z(S&P)	Z(TED)	Z(dLevel)
Alpha (p.a.)	1.43%	1.63%	2.53%	2.30%	1.58%	1.22%	2.00%
t-value	*(1.00)*	*(1.32)*	*(1.72)**	*(2.00)***	*(1.19)*	*(1.08)*	*(1.89)**
OMX	0.21	0.21	0.19	0.24	0.21	0.22	0.21
t-value	*(10.20)***	*(9.07)***	*(7.26)***	*(13.84)***	*(11.00)***	*(12.72)***	*(9.89)***
SMB		0.13	0.15	0.18	0.18	0.14	0.16
t-value		*(3.32)***	*(3.26)***	*(4.70)***	*(4.85)***	*(4.00)***	*(5.22)***
HML		0.02					
t-value		*(0.52)*					
LS1			0.003				
t-value			*(0.25)*				
LS2			-0.003				
t-value			*(-0.35)*				
LS3			-0.004				
t-value			*(-0.59)*				
Spread			0.004				
t-value			*(0.60)*				
Yield			0.009				
t-value			*(1.12)*				
Gamma 1				-0.330	-1.076	-0.136	0.192
t-value				(-1.30)	*(-1.84)**	*(-4.84)***	*(5.02)***
Gamma 2				-0.884	-0.410	-0.094	0.207
t-value				*(-2.56)***	*(-0.84)*	*(-2.02)***	*(4.63)***
Delta 1				-0.117	1.450	0.089	-0.028
t-value				*(-3.07)***	*(2.99)***	*(3.65)***	*(-0.07)*
Delta 2				0.430	-2.215	0.048	0.922
t-value				*(1.84)**	*(-1.84)**	*(0.91)*	*(1.95)**
Adj. R^2	0.62	0.72	0.69	0.77	0.76	0.79	0.79

* p<0.10; ** p<0.05

p-val total				0.00%	0.39%	0.00%	0.00%
p-val daily				4.31%	1.22%	0.00%	0.40%

The table shows the results from the OLS regression of the Hedge Fund Equity Index, using White robust standard errors. Alphas have been annualised. In the Fung and Hseih regression, "LS" stands for the lookback straddles ABS factors. There are 64 observations per regression. The last two rows of the table are the p-values for the hypothesis tests (8) and (9).

Fixed Income Index

	CAPM	Fama & French	Fung & Hseih	Time-varying models			
				Z(VIX)	Z(S&P)	Z(TED)	Z(dLevel)
Alpha (p.a.)	1.16%	1.31%	1.40%	1.12%	0.39%	1.06%	1.30%
t-value	*(0.85)*	*(0.98)*	*(0.91)*	*(0.74)*	*(0.24)*	*(0.75)*	*(0.96)*
OMX	0.03	0.03	0.04	0.04	0.05	0.03	0.05
t-value	*(1.59)*	*(1.13)*	*(1.49)*	*(1.68)**	*(1.71)**	*(1.49)*	*(-1.62)*
SMB		0.03	0.03	0.04	0.03	0.03	0.03
t-value		*(0.97)*	*(0.89)*	*(1.19)*	*(1.08)*	*(0.84)*	*(-1.25)*
HML		0.06					
t-value		*(1.43)*					
LS Bond			-0.01				
t-value			*(-0.99)*				
LS Currency			0.008				
t-value			*(1.12)*				
LS Commodity			-0.004				
t-value			*(-0.38)*				
Spread			0.004				
t-value			*(1.15)*				
Yield			-0.002				
t-value			*(-0.23)*				
γ(1)				-0.001	-0.070	-0.035	0.038
t-value				(-0.20)	*(-0.15)*	*(-0.70)*	*(0.63)*
γ(2)				0.002	0.085	0.014	0.006
t-value				*(0.20)*	*(0.18)*	*(0.31)*	*(0.11)*
δ(1)				-0.001	0.043	0.025	-0.193
t-value				*(-0.17)*	*(0.07)*	*(0.54)*	*(-0.44)*
δ(2)				-0.001	1.547	-0.065	-1.051
t-value				*(-0.20)*	*(0.99)*	*(-0.90)*	*(2.22)***
Adj. R^2	0.02	0.04	-0.04	-0.03	0.00	0.00	0.01
* $p<0.10$; ** $p<0.05$							
p-val total				46.38%	18.42%	67.00%	60.59%
p-val daily				17.10%	48.36%	72.63%	27.27%

The table shows the results from the OLS regression of the Hedge Fixed Income Index, using White robust standard errors. Alphas have been annualised. In the Fung and Hseih regression, “LS” stands for the lookback straddles ABS factors. There are 64 observations per regression. The last two rows of the table are the p-values for the hypothesis tests (8) and (9).

Fund of Funds

	CAPM	Fama & French	Fung & Hseih	Time-varying models			
				Z(VIX)	Z(S&P)	Z(TED)	Z(dLevel)
Alpha (p.a.)	-0.50%	-0.42%	-0.42%	0.73%	0.80%	-0.33%	-0.18%
t-value	*(-0.35)*	*(-0.34)*	*(-0.32)*	*(0.64)*	*(0.61)*	*(-0.29)*	*(-0.15)*
OMX	0.10	0.11	0.09	0.10	0.09	0.10	0.09
t-value	*(4.96)***	*(4.18)***	*(3.35)***	*(4.19)***	*(3.77)***	*(4.35)***	*(4.98)***
SMB		0.15	0.14	0.12	0.10	0.11	0.12
t-value		*(4.23)***	*(3.40)***	*(3.69)***	*(3.35)***	*(3.44)***	*(4.09)***
HML		-0.04					
t-value		*(-0.8)*					
LS1			0.00				
t-value			*(-0.03)*				
LS2			-0.005				
t-value			*(-0.66)*				
LS3			-0.002				
t-value			*(-0.19)*				
Spread			-0.005				
t-value			*(-1.29)*				
Yield			0.001				
t-value			*(0.09)*				
Gamma 1				-0.793	0.261	-0.067	0.151
t-value				*(-3.32)***	*(0.42)*	*(-2.92)***	*(1.88)**
Gamma 2				-0.180	0.038	0.212	-0.082
t-value				*(-0.62)*	*(0.07)*	*(4.78)***	*(-1.36)*
Delta 1				0.391	-1.325	0.074	0.834
t-value				*(1.93)**	*(-1.55)*	*(3.60)***	*(1.87)**
Delta 2				0.387	1.005	-0.188	0.441
t-value				*(-1.53)*	*(0.71)*	*(-3.25)***	*(0.65)*
Adj. R^2	0.27	0.49	0.49	0.56	0.52	0.55	0.54
* p<0.10; ** p<0.05							
p-val total				0.01%	2.37%	0.00%	1.74%
p-val daily				0.82%	90.41%	0.00%	1.86%

The table shows the results from the OLS regression of the Hedge Fund Fund-of-Fund Index, using White robust standard errors. Alphas have been annualised. In the Fung and Hseih regression, “LS” stands for the lookback straddles ABS factors. There are 64 observations per regression. The last two rows of the table are the p-values for the hypothesis tests (8) and (9).

Multi Strategy

	CAPM	Fama & French	Fung & Hseih	Time-varying models			
				Z(VIX)	Z(S&P)	Z(TED)	Z(dLevel)
Alpha (p.a.)	2.41%	2.50%	3.28%	1.77%	1.34%	2.37%	2.54%
t-value	*(1.52)*	*(1.78)**	*(2.11)***	*(1.12)*	*(0.75)*	*(1.72)**	*(1.69)*
OMX	0.16	0.16	0.18	0.15	0.16	0.15	0.15
t-value	*(6.89)***	*(5.40)***	*(5.27)***	*(5.61)***	*(4.49)***	*(5.97)***	*(4.52)***
SMB		0.13	0.16	0.17	0.14	0.16	0.14
t-value		*(3.53)***	*(4.84)***	*(5.38)***	*(4.29)***	*(4.95)***	*(4.56)***
HML		-0.03					
t-value		*(-0.65)*					
LS1			0.02				
t-value			*(2.61)***				
LS2			-0.001				
t-value			*(-0.16)*				
LS3			0.000				
t-value			*(0.03)*				
Spread			0.006				
t-value			*(1.61)*				
Yield			0.000				
t-value			*(0.00)*				
Gamma 1				-0.333	0.095	-0.040	0.067
t-value				*(-1.21)*	*(0.19)*	*(-0.38)*	*(0.53)*
Gamma 2				0.530	1.009	-0.066	0.044
t-value				*(1.21)*	*(1.81)**	*(-0.69)*	*(0.38)*
Delta 1				0.319	-0.161	0.067	0.260
t-value				*(1.49)*	*(-0.22)*	*(0.76)*	*(0.48)*
Delta 2				-0.884	1.126	0.076	-0.266
t-value				*(-2.13)***	*(0.65)*	*(0.66)*	*(-0.32)*
Adj. R^2	0.42	0.53	0.54	0.55	0.55	0.54	0.51
* p<0.10; ** p<0.05							
p-val total				1.46%	3.73%	38.52%	80.00%
p-val daily				23.67%	20.15%	56.25%	85.79%

The table shows the results from the OLS regression of the Hedge Fund Multi-Strategy Index, using White robust standard errors. Alphas have been annualised. In the Fung and Hseih regression, “LS” stands for the lookback straddles ABS factors. There are 64 observations per regression. The last two rows of the table are the p-values for the hypothesis tests (8) and (9).

Managed Futures

	CAPM	Fama & French	Fung & Hseih	Time-varying models			
				Z(VIX)	Z(S&P)	Z(TED)	Z(dLevel)
Alpha (p.a.)	2.57%	2.83%	3.85%	1.83%	1.37%	2.98%	2.48%
t-value	*(1.55)*	*(1.86)**	*(2.58)***	*(1.05)*	*(0.76)*	*(2.04)***	*(1.63)*
OMX	0.20	0.19	0.21	0.19	0.22	0.20	0.19
t-value	*(8.19)***	*(7.77)***	*(8.16)***	*(8.91)***	*(8.88)***	*(10.66)***	*(7.99)***
SMB		0.10	0.16	0.16	0.14	0.14	0.14
t-value		*(2.72)***	*(3.69)***	*(3.27)***	*(3.30)***	*(4.00)***	*(3.15)***
HML		0.06					
t-value		*(1.33)*					
LS1			0.02				
t-value			*(2.31)***				
LS2			0.002				
t-value			*(0.23)*				
LS3			-0.002				
t-value			*(-0.24)*				
Spread			0.005				
t-value			*(1.22)*				
Yield			0.006				
t-value			*(0.69)*				
Gamma 1				0.397	-0.308	0.027	-0.016
t-value				*(1.39)*	*(-0.70)*	*(0.45)*	*(-0.31)*
Gamma 2				-0.002	-0.301	-0.111	0.111
t-value				*(0.00)*	*(-0.60)*	*(-1.72)**	*(1.64)*
Delta 1				-0.317	1.262	-0.081	0.229
t-value				*(-1.36)*	*(2.29)***	*(-1.56)*	*(0.42)*
Delta 2				-0.391	0.126	0.157	-0.849
t-value				*(-0.76)*	*(0.09)*	*(1.81)**	*(-1.17)*
Adj. R^2	0.51	0.58	0.61	0.59	0.58	0.60	0.60

* p<0.10; ** p<0.05

p-val total	7.32%	0.05%	3.69%	0.09%
p-val daily	32.66%	57.63%	12.41%	8.58%

The table shows the results from the OLS regression of the Hedge Fund Managed Futures Index, using White robust standard errors. Alphas have been annualised. In the Fung and Hseih regression, "LS" stands for the lookback straddles ABS factors. There are 64 observations per regression. The last two rows of the table are the p-values for the hypothesis tests (8) and (9).