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Do Swedish hedge funds outperform the market?

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ABSTRACT

Using return data during the period February 2004 to January 2007 we examine abnormal performance for 16 Swedish hedge funds. In order to do this we estimate individual Jensen alphas employing three different asset pricing models; the CAPM, the Fama-French three-factor model and a conditional six-factor model. The time-varying six-factor model is based on factors and instruments in a combination never previously used for this purpose. We find that none of the studied hedge funds have delivered returns that could not be explained by the utilized models. Furthermore, we argue that the CAPM and the Fama-French three-factor model are inappropriate when it comes to evaluating hedge fund performance due to poor explanatory power. The additional factors and the ability to account for time-varying factor exposure in the six-factor model makes it superior at explaining the dynamic trading strategies associated with hedge funds.

Keywords: Hedge funds, Time series regression, Asset pricing model, Performance measure.

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1. INTRODUCTION

In this chapter we aim to introduce the reader to the area of research that this thesis attempt to discuss. The background provides a general discussion of the topic and leads up to a problem specification. This, in turn, constitutes the foundation for the thesis' purpose. Further on, limitations and outline will be presented.

1.1 BACKGROUND

During the last decade a sharp increase in the interest for alternative investments has been evident. This development has consequently cast much light on hedge funds, private equity and real estate. These, in popularity, rapidly growing investment vehicles provide an alternative to fixed-income and equity investments. The reasons for this is that investors are becoming more and more sophisticated and thus constantly search for new ways to pursue different goals. These might be to diversify, hedge or increase exposure to a certain asset etc. This new focus has, somewhat surprisingly, been recent despite the fact that hedge funds have been in existence for more than 50 years.

A main attractive feature of hedge funds is that their regulation allows for a wide spectrum of different investment and trading strategies to be used. Hedge fund managers can for example use derivatives, leverage and short positions and therefore they are considered to be sources of absolute returns independent of market movement. In addition, they commonly employ dynamic trading strategies which allow them to instantly adapt to or benefit from changing circumstances.

Estimations suggest that roughly 9000 hedge funds controlling over 1, 1 trillion USD are active world-wide. Nevertheless, the growth continues with new hedge funds being launched constantly to meet a surging demand from investors. Furthermore, an increasing amount of attention in financial and academic literature has been evident lately. In the light of the facts mentioned above we feel that further thorough research in this field is justified.

1.2 PROBLEM SPECIFICATION

If we compare the Swedish hedge fund market with the US market it appears to be different, in the sense that it is relatively young and small. Yet, the Swedish market is regarded as one of the fastest growing in the world (Anderlind et al [2003]). The fact of its size and high growth makes it an interesting market to study.

To analyse hedge fund performance researchers often use asset pricing models such as the CAPM, the Fama-French three-factor model and various multi-factor models. Traditionally, these models have been static, recent research however suggests that unconditional models are unable to capture the dynamic nature of hedge funds. As a consequence academic focus has started to shift to conditional models. A particular way to account for time-variability that has gained support lately is the use of instrumental variables to be able to condition factor exposure on publicly known information. Nevertheless, relatively few studies have been carried out so far.

As the amounts invested in hedge funds continues to grow it ought to be of substantial interest, not the least from an investors' point of view, to investigate if these funds generate abnormal returns.

1.3 PURPOSE

The purpose of this master thesis is to determine whether Swedish hedge funds generate returns in excess of what can be explained by the asset pricing models employed.

1.4 LIMITATIONS

In this thesis we study return data on Swedish hedge funds collected from the Reuters database, hence the available data is restricted to this databases' sample. Our selection criteria are that the funds have their domicile in Sweden as well as a sufficient return history. Our requirement of return history is 36 months which follows previous studies (see section 3.3.1). This leaves us with a sample-period from February 2004 to January 2007. The selection criteria give us a total sample of 16 individual hedge funds. It is above all the requirement of a 36 month return history that limits our sample. However, several funds have been excluded due to the fact that they are registered offshore even though they are managed from Sweden.

We will restrict our analysis to three asset pricing models; the CAPM, the Fama-French three factor model and a conditional six-factor model. This is mainly due to lack of space. Nonetheless, we will report goodness of fit statistics for a conditional version of the Fama-French three factor model and for a static version of the six-factor model.

1.5 OUTLINE

The thesis begins with some background to the selected topic. The chapter continues with a problem discussion and an account of purpose and limitations. In chapter two, we will provide an introduction to hedge funds, their market and the previous research performed within this field. Further on we describe the theoretical framework which constitutes the basis for our analysis and conclusion. In the following chapter three, we clarify the empirical method and specify the asset pricing models employed. A description of the data material can also be obtained from here. In chapter four we present and discuss the results from statistical tests and regression estimates. Chapter five concludes the thesis with a summary of the results, our conclusion and suggestions for further studies.

2. THEORETICAL FRAMEWORK

In the following chapter we will give an account of relevant theories. First we will provide an overview of the hedge fund market followed by a definition of hedge funds and compare these to traditional investment funds. Thereafter we will present some results from previous studies on hedge fund performance followed by a description of the asset pricing models and performance measures employed in the thesis. The chapter is concluded with statistical properties of importance.

2.1 HEDGE FUND MARKETS

The creation of the hedge fund is commonly accredited to Alfred Winslow Jones, a journalist who turned fund manager when assigned to *Fortune magazine* in 1949. Jones came up with an idea when working on his article "Fashions in Forecasting"; he could go long in undervalued stocks and at the same time short-sell stocks that was overvalued. It occurred to him that this strategy was beneficial no matter which way the market went (Brown et al. [1999]). Jones set up an investment fund as a general partnership, this allowed him take long positions in undervalued stocks which would be offset and partially funded by taking short positions in others. In fact this was probably the first time anyone had combined both long and short positions using leverage to increase return, and thereby creating the notion of a market neutral position. This idea was new and revolutionary in the financial world at the time. Although this strategy was ground-breaking hedge funds had a slow start and it was not until 1980´s that their numbers really escalated (Anderlind et al. [2003]). Today the number of hedge funds and the capital controlled by these funds has reached enormous proportions. At the time being estimations indicate that about 9000 hedge funds exists world-wide, managing over 1.1 trillion USD[1]. Nevertheless, new hedge funds are being launched every day to meet a surging demand for this type of investment vehicle.

Today the United States are home to roughly 80 percent of all hedge funds in the world. The first hedge fund was established in New York, one of the main financial centers' of the world, and still about 35 percent of all active hedge funds operate from here. The Asian and the European hedge fund markets are still new and relatively small, however, they are the markets with the highest current growth rate according to Anderlind et al. (2003).

[1] The Hedge Fund Association

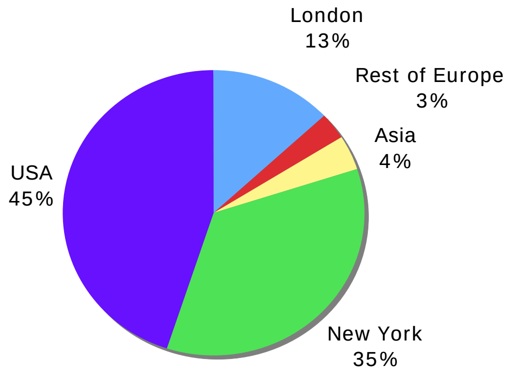

Figure 2.1 Geographic locations of hedge funds (Anderlind et al. [2003]).

Figure 2.1 indirectly give an idea of how small the Swedish hedge fund market is from an international perspective, it wasn't until 1996 that the first hedge fund started its operations in Sweden. Still, it took nearly four years until a real hedge fund market was in place. One main reason to why it took such a long time for a market to be established in Sweden was the lack of knowledge about this form of investment (Anderlind et al. [2003]). The large amount of money that is required when investigating in a hedge fund is a further reason, a minimum amount can be 500 thousand SEK or more. At the present Sweden is one of the top growing markets from an international point of view, today there are roughly 60 hedge funds in the Swedish market, which holds about 66 billion SEK[2].

In order to profit from loser regulations and e.g. more beneficial tax-systems many hedge funds have chosen to register their operations offshore. Their domiciles are commonly Cayman Islands, British Virgin Island and Bermuda among others. These countries are generally closed markets, in the terms of publicly available information regarding operations of various investment vehicles. As a consequence, the actual number of active hedge funds in the world is difficult to estimate (Anderlind et al, [2003]).

[2] The Swedish Central Bank

2.1.1 Hedge fund definition

If we examine the nomenclature "hedge fund" it leads us to the original definition of the word "hedge", which is to decrease risk by taking on an asset position that offsets an active source of risk. One definition of a hedge fund might be an actively managed, mutual investment vehicle that is exposed to only a limited set of investors and whose performance is measured in absolute return units. In spite of this plain definition we exclude some hedge funds and include some funds that are obviously not hedge funds by using it. There exist nearly as many definitions of a hedge fund as there are hedge funds. E.g. a trader that is holding a large position in a specific stock can hedge the market component of the stock's risk by taking a short position in equity index futures. If another investor holds a large position in foreign equities, he can hedge the portfolio's currency risk through buying currency put options.

It is possible to broadly define a hedge fund by saying that it is an information-motivated fund that hedges away almost all sources of risk that is not associated with the risk that the fund wants to be exposed to. Below follows some various hedge fund definitions to high-light the differences.

"*A privately organized, pooled investment vehicle. Investing primarily in publicly traded securities and derivatives on publicly traded securities. Using short positions, long positions, and leverage in combination to reduce exposure to moves in the broad market and focus on profiting from security selection*." (Crowley & Purcel. [1999])

"*An aggressively managed portfolio of investments that uses advanced investment strategies such as leverage, long, short and derivative positions in both domestic and international markets with the goal of generating high returns (either in an absolute sense or over a specified market benchmark). Legally, hedge funds are most often set up as private investment partnerships that are open to a limited number of investors and require a very large initial minimum investment. Investments in hedge funds are illiquid as they often require investors keep their money in the fund for a minimum period of at least one year.*"[3]

[3] Investopedia

As is evident there are quite a few differences in the definitions and is it hard to say that one definition is more accurate than the other. The conclusion is that there is no absolute definition of hedge funds. For that reason it has become more customary to define hedge funds by their characteristics.

The key characteristics of hedge funds have been stated by Cottier (1997). He argues that there are no restrictions regarding the choice of asset class/classes to invest in and moreover they can settle on whatever market they prefer. This means that hedge funds can invest in practically any financial instrument, including stocks, private equity, futures, options, derivates, bonds, commodities, currencies, and venture capital (McCrary [2002]). In doing this they are trying to create a portfolio that is unbound by the market development. The purpose is to reach a balanced risk level and reduce the market risk and at the same time achieve absolute return. Through combining long and short positions and at the same time hold liquid assets this can be achieved.

A long position benefits from a rise in the securities price as opposed to a short position which gains from a falling security price. A skilled fund manager can obtain a positive yield from a combination of long and short positions independent of the market movement (Anderlind et al. [2003]).

Furthermore, hedge funds have free placement rules and can thus employ dynamic trading strategies to be able to adapt to changing environments. We will elaborate on the different strategies further on in this chapter. Table 2.2 summarizes the key characteristics of hedge funds.

Reduce market risk.	Free choice of trading strategy.
Create a balanced risk level.	Invest in both currencies and derivatives.
Not restricted to one asset class.	Market of choice.
Managers invest in their own fund.	Free placement rules.
The ability to use long and short positions.	Strive for absolute positive return.
High minimum investments.	Performance based fees.

Table 2.2 Key characteristics of hedge funds.

2.1.2 Hedge funds versus traditional investment funds

Table 2.3 is an excerpt from Anderlind et al. (2003) and points out differences between traditional investment funds and hedge funds

	Hedge funds	**Traditional funds**
Placement rules	Free placement rules	Limited placement rules
Yield Requirements	Absolute positive yield	Relative yield
The view on risk	Lose money	Differ from index
Measure of success	High return due to risk	Outperform market index
Fund manager has his own money invested in the fund	Very common	Not common
Fee structure	Fixed fees and performance based fees	Fixed fees

Table 2.3 Differences between traditional investment funds and hedge funds.

2.1.3 Hedge fund investment strategies

The subsequent description of hedge fund strategies is an exact excerpt from Agarwal & Naik (2000). The strategies are commonly divided into two sub-groups, directional and non-directional.

Non-directional strategies

These strategies do not depend on the direction of any particular market movement and are usually referred to as market-neutral strategies. They are designed to exploit short-term market inefficiencies and pricing discrepancies between related instruments while hedging away as much of the market exposure as possible. The trades often suffer from poor liquidity why funds following these strategies typically run smaller pools of capital than their counterparts following directional strategies. Included in the group of non-directional strategies are:

1. *Fixed Income Arbitrage* is a strategy having long and short bond positions via cash or derivatives markets in government, corporate, and/or asset-backed securities. Risk varies depending on duration, credit exposure, and the degree of leverage employed.

2. *Event Driven* is a strategy that benefits from mispricing arising in different events such as merger arbitrage and restructurings. The manager takes a position in an undervalued security that is anticipated to rise in value because of events such as mergers, reorganizations, or takeovers. The main risk is non-realization of the event.

3. *Equity Hedge* is a strategy of investing in equity or equity-like instruments where the net exposure (gross long minus gross short) is generally low. The manager may invest globally, or have a more defined geographic, industry, or capitalization focus. The risk primarily pertains to the specific nature of the long and short positions.

4. *Restructuring* is a strategy of buying and occasionally shorting securities of companies under Chapter 11 and/or ones that are undergoing some form of reorganization. The securities range from senior secured debt to common stock. The liquidation of financially distressed companies is the main source of risk in these strategies.

5. *Event Arbitrage* is a strategy of purchasing securities of a company being acquired and shorting that of the acquiring company. The risk associated with such strategies is more of a "deal" risk than a market risk.

6. *Capital Structure Arbitrage* is a strategy of buying and selling different securities of the same issuer (e.g. convertibles/common stock) and seeking to obtain low volatility returns by arbitraging the relative mispricing of these securities.

Directional strategies

These strategies benefit from broad market movements. The following are popular directional strategies:

1. *Macro* is a strategy that seeks to capitalize on country, regional, and/or economic change affecting securities, commodities, interest rates, and currency rates. Asset allocation can be aggressive, and leverage and derivatives may be utilized. The method and degree of hedging can vary significantly.

2. *Long* is a strategy that employs a "growth" or "value" approach to investing in equities with no shorting or hedging to minimize inherent market risk. These funds mainly invest in emerging markets where there may be restrictions on short sales.

3. *Hedge (Long Bias)* is a strategy similar to an equity hedge with significant net long exposure.

4. *Short* is a strategy that focuses on selling short over-valued securities, with the hope of repurchasing them in the future at a lower price.

To give an overview of how the different strategies differ from each other we will present the most common hedge fund strategies in table 2.4 below.

Investment alternative /Strategy approach	Equity	Fixed-income	Derivatives
Market depending	Long/ short equity hedge	Long/ short FX hedge	Tactical derivative strategies
Market independent	Equity arbitrage	FX arbitrage	
Opportunistic	Multi strategies		

Table 2.4 Hedge fund strategies (Anderlind et al. [2003]).

The matrix illustrates the combination between different investment alternatives (equity, fixed-income and derivatives) and strategy approach (market depending, market independent and opportunistic) for the hedge fund strategies. However, no fixed boundaries exist, e.g. a long equity hedge fund might invest in fixed-income as well. The strategy classification merely states the main focus of the fund.

2.2 PREVIOUS STUDIES

Although much focus has been placed on the hedge fund industry lately, due to its recent growth, relatively few studies on their performance have been carried out in comparison with other investment tools like mutual funds. This may partly be explained by the lack of transparency in the industry and hence the difficulties associated with retrieving return data on hedge funds. Nevertheless, the significant growth of hedge funds during the 1990s resulted in a number of studies on hedge fund performance, (Ackermann, McEnally & Ravenscraft [1999]; Brown, Goetzmann & Ibbotson [1999]; Edwards & Caglayan [2001]; Kat & Miffre [2003]; Liang [1999]), to mention a few.

Brown et al. (1999) studied annual return data on offshore hedge funds using unconditional CAPM and found positive excess returns (alpha) for a majority of the funds (40% had significant alphas). By comparing hedge fund returns to the S&P500 index during 1988 to 1995 Ackermann et al. (1999) found that hedge funds are unable to consistently beat the market when absolute or total risk adjusted return are used. Their result suggests that hedge funds are able to outperform the market on a gross return basis. However, their ability to earn superior gross return is, on average, equal to the administrative and incentive fee. Furthermore, they argue that although hedge funds have little to offer over indexing, their low beta values make them a potentially valuable addition to many investors' portfolios. Kat & Miffre (2003) employed both conditional and static six-factor models to evaluate hedge fund performance during the period 1990 to 2000 and found that at least 80 % of the funds exhibited positive abnormal performance using the conditional model. The authors argue that allowing for conditioning information increases the measures of abnormal performance, both in statistical and economic terms. Furthermore, they claim that hedge funds perform particularly well in down-markets. Liang (1999) employed a static eight-factor model to estimate alphas between January 1992 through December 1996 for equally weighted hedge fund indexes and concluded that alphas change by investment style, ranging from -5, 22% to 1, 26%. Seven out of his 16 studied indexes produced positive significant alphas. Using monthly return data during the period January 1990 through August 1998, Edwards & Caglayan (2001) estimate static six-factor alphas for individual hedge funds. The study concludes that, on average, hedge funds earn positive excess returns (8, 52% annually), but these returns differ substantially between investment strategies. Out of the entire sample, 25% of the funds displayed significant positive alphas.

A majority of the previous' studies use average returns, equally weighted or value-weighted indexes of all hedge funds or funds within a particular investment style, to estimate alphas. Although this procedure might be informative for investor's seeking to invest in hedge fund indexes, it does not provide answers to the question examined in this study. In addition, it is common knowledge that hedge funds, even within the same strategy, might have substantially different exposures. Hence, employing average returns to estimate alphas is likely to be improper since it implicitly forces all funds to have identical factor loadings. To be able to answer the question posed in this thesis we estimate alphas by examining individual hedge fund returns and as a direct consequence we allow for individual factor loadings.

2.3 ASSET PRICING MODELS

A factor model decomposes an asset's return into asset common factors. These common factors are interpreted as capturing fundamental risk components and the factor model measures an asset's sensitivities to these risk factors. Factor models are used for different purposes:

- Estimating abnormal returns
- Estimating variance and covariance between asset returns
- Forecasting returns
- Identifying risk sensitivities

This study will, as mentioned above, focus on estimating abnormal returns. Nevertheless, a discussion of the various hedge funds exposure to the model risk factors is inevitable.

2.3.1 CAPM

The Capital Asset Pricing Model, developed by William Sharpe (1964), John Lintner (1965) and Mossin (1966) in the 1960's, is a one-factor model stating that a security's beta (sensitivity to the market risk premium) is sufficient to explain that security's return. According to the Capital Asset Pricing Model the expected return of a security or a portfolio of securities equals the risk free rate plus a market risk premium.

$$E[r_{it}] = r_{ft} + \beta_i (r_{mt} - r_{ft}) \quad (1)$$

- $E[r_{it}]$ is the expected return of the asset
- r_{ft} is the risk-free rate of return
- β_i is the assets' sensitivity to the market portfolio. The definition of Beta is:

  $$\beta_i = \frac{Cov(r_{mt}, r_{it})}{\sigma_m^2} \quad (2)$$

- $(r_{mt}\text{-}r_{ft})$ is the market risk premium, i.e. the compensation required by an investor for taking on the risk associated with the market portfolio.

Beta is a measure of a security's volatility or systematic risk in comparison with the market portfolio. Securities or portfolios that is riskier than the market, has a beta larger than one and accordingly a beta less than one means that the security will be less volatile than the market. The higher the beta the higher the expected return.

2.3.2 Fama-French three-factor model

Eugene Fama and Kenneth R. French (1992) developed a three-factor model to better be able to explain asset returns over time. As in the Capital Asset Pricing Model the market risk premium is a factor, the additional factors are small (cap) minus big and high (book/market) minus low.

$$E[r_{it}] = r_{ft} + b_{1i,t}(r_{mt} - r_f) + b_{2i,t}(SMB) + b_{3i,t}(HML) \tag{3}$$

Fama and French discovered that two classes of stocks tended to do better than the market as a whole, those were small caps and stocks with high book-to-market ratio. They added two factors to CAPM to reflect a portfolio's exposure to these two classes. Fama and French demonstrated in their (1992) article that this three-factor model is superior to the CAPM in explaining asset returns.

However, there is controversy over why firm-specific attributes like the Fama-French factors should predict returns. Fama & French (1995, 1996) argue that these factors are proxies for exposure to underlying economic risk factors that are rationally priced in the market. Another way of saying this is that the characteristics are proxies for non-diversifiable factor risk. Others, (e.g. Haugen & Baker [1996] and Daniel & Titman [1997]) claim that such variables should be used to identify securities that are systematically mispriced by the market. A third view, advocated by e.g. Black (1993) is that the observed predictability is mainly due to data snooping and various biases in the data.

2.3.3 Conditional six-factor model

Aiming to improve our ability to capture the hedge funds' risk exposure we developed a time-varying six-factor model based on the Fama-French three-factor model.

$$E[r_{it}] = r_{ft} + b_{1i,t}(r_{mt} - r_f) + b_{2i,t}(SMB) + b_{3i,t}(HML) +$$
$$+ b_{4i,t}(TERM) + b_{5i,t}(JPGBI) + b_{6i,t}(MT), \quad (4)$$

where TERM is the monthly return on a long-term government bond portfolio minus the one-month lagged 30-day T-bill return. JPGBI is the return on a global bond index. MT is the maximum of zero and the excess return on the market portfolio.

There are a number of reasons why a conditional model potentially does a better job in explaining hedge fund returns than an unconditional model. Gupta et al. (2003) argues that most hedge funds follow dynamic investment strategies with strongly fluctuating risk exposures through time. This is supported by Ferson & Shadt (1996) who found evidence suggesting that the trading behavior of fund managers result in more complex dynamics than even those of the underlying assets that they trade. They claim that unconditional models are likely to be unreliable if expected returns and risks vary over time. It is therefore reasonable to believe that inferences from a time-varying model differ significantly from inferences from conditional models.

Ferson & Harvey (1999) developed a model to estimate conditional asset pricing models. The idea is to model time-varying parameters as linear functions of predetermined instruments. These instruments are supposed to be proxies for economy-wide variables, e.g. business cycles. The authors assume the following general model for the conditional returns and the betas:

$$E_t(r_{i,t+1}) = \alpha_{it} + \beta_{it}^{'} E_t(r_{p,t+1})$$
$$\beta_{it} = b_{0i} + b_{1i}^{'} Z_t$$
$$\alpha_{it} = \alpha_{0i} + \alpha_{1i}^{'} Z_t \quad (5)$$

- $r_{i,t+1}$ is the return for any stock or portfolio *i*, net of the return on a one-month Treasury bill
- $r_{p,t+1}$ is a vector of excess returns on the risk factor-mimicking portfolios
- Z_t is a vector of mean zero information variables known at time t

- α_{it} is a measure of abnormal return on the asset.
- b_{0i} can be interpreted as an "average beta", in other words the unconditional mean of the conditional beta.
- β_{it} is the response coefficients of the conditional beta with respect to the information variables Z_t.

In equation (5) the relation over time between the instruments and the betas for a given portfolio is assumed to be a fixed linear function, as b_{1i} is a fixed coefficient. By combining the above equations the following econometric model is formulated:

$$r_{it+1} = (\alpha_{0i} + \alpha_{1i}^{'} Z_t) + (b_{0i} + b_{1i}^{'} Z_t) r_{p,t+1} + \varepsilon_{i,t+1} \tag{6}$$

2.3.4 Risk factors

In the following we will give our motives for including the various risk factors.

- **r_m:** Inclusion is motivated by the CAPM which says that assets return can be fully explained by its sensitivity to the market portfolio.
- **SMB:** A Fama-French factor which attempts to capture the proven circumstance, see Fama & French (1992), that a small firm has a higher return than a large firm. A plausible explanation for this is that smaller firms are riskier.
- **HML:** A Fama-French factor based on the notion that at high book-to-market ratio is related to a high return.
- **TERM:** This factor is meant to capture the market risk in bond returns due to unexpected interest rate changes. The T-bill rate might be viewed upon as a long-run proxy for the expected return on bonds; in this case TERM will reflect the deviation of long-term bond returns from expected returns (see Edwards & Caglayan [2001]).
- **JPGBI:** Included due to the fact that hedge funds invest in bond indexes (Kooli [2005])
- **MT:** This factor attempts to account for the possibility that hedge fund managers exhibit a market timing ability (Gupta et Al. [2003]). However, empirical evidence seems to indicate that this ability is rare (Kon[1983], Chang & Lewellen[1984], Henriksson[1984])

2.3.5 Instruments

The used instruments are the following:

- **GDP** is the Swedish gross domestic product.
- **TCW** is an index measuring the development of the exchange rate between the Swedish krona (SEK) and a basket of other currencies.

Although we have not found any previous studies where these information variables have been used we believe that they should be good business-cycle proxies. The GDP is clearly related to the state of the Swedish economy as a whole whereas TCW is foremost linked to the domestic interest rate level.

2.4 PERFORMANCE MEASURES

To be able to determine whether Swedish hedge funds deliver superior returns or not we need to measure their performance. Or main focus is on the intercept from the regression models, traditionally called Jensen's alpha. However, the Sharpe ratio will also be reported.

2.4.1 Jensen's performance index

Jensen's index is given by the intercept α from e.g. the following regression model (see for example Asgharian[2006]):

$$E[r_i] - r_f = \alpha_i + \beta_i (E[R_m] - R_f) \qquad (7)$$

An alpha equal to zero implies the standard CAPM. Jensen's alpha is a measure of abnormal return on the asset or portfolio, a positive alpha implies a positive abnormal return.

2.4.2 Sharpe's performance index

The Sharpe ratio measures the expected return per unit of risk and is defined as (see for example Asgharian [2006]):

$$sr_i = \frac{E[r_i] - r_f}{\sigma_i} \qquad (8)$$

This ratio is the slope of the line between the risk free asset (r_f, 0) and the portfolio i ($E[r_i]$,σ_i). The tangency portfolio is the portfolio with maximum Sharpe ratio. If CAPM holds the market portfolio is the tangency portfolio and lies on the efficient frontier.

2.5 STATISTICAL PROPERTIES

In order to estimate our three different models we have to be aware of some important statistical properties. This thesis is based on time-series data and it is essential to determine whether it has certain unwanted characteristics that might affect validity. More specifically, if we find evidence of heteroscedasticity and/or autocorrelation within the data, the OLS-estimator will no longer be the optimal estimator. It will still be linear and unbiased, but not efficient, hence it is no longer BLUE (*Best Linear Unbiased Estimator*). The consequences due to this will turn out to be that the confidence intervals and hypothesis tests can be misleading. If we detect heteroscedasticity and/or autocorrelation in our time series we will have to make certain adjustments. One way of doing this is to employ the Newey-West robust estimator with OLS. This estimator was developed by Newey and West (1987) and is a variance-covariance estimator that is reliable in the presence of both heteroscedasticity and autocorrelation. A further aspect to consider is the degree of correlation between the explanatory variables in a model. If variables are highly correlated, or in other terms multicollinearity is present, this will in effect lead to a spurious regression. Below we will provide a more detailed account of these statistical properties.

2.5.1 Heteroscedasticity

If the variance of the regression errors is constant through time, we say that the residuals are homoscedastic. The opposite, i.e. when the variances of the residuals vary over time, is known as heteroscedasticity (see for example Brooks [2002]). Several tests are applicable to test for heteroscedasticity. One popular test is White's, the test is particularly useful since it make few assumptions about the likely form of the heteroscedasticity i.e. the test is a general test and therefore seem to fit our requirements. In White's test the null hypothesis is that no heteroscedasticity can be found within the data material. The test statistic is calculated from an auxiliary regression, White (1980), where the squared residuals are regressed on all possible cross products of the regressors. To illustrate how the test is carried out we estimate the following regression:

$$y_t = \beta_1 + \beta_2 x_{2t} + \beta_3 x_{3t} + \varepsilon_t \tag{9}$$

The hypothesis we want to test is if ε_t is homoscedastic against that it is heteroscedastic:

H_0 : Homoscedastic
H_1: Heteroscedastic

To start the test we estimate equation (9) with OLS and save the residual $\hat{\varepsilon}_t$ the test statistic is afterwards built on the auxiliary regression:

$$\hat{\varepsilon}_t^2 = \alpha_1 + \alpha_2 x_{2t} + \alpha_3 x_{3t} + \alpha_4 x_{2t}^2 + \alpha_5 x_{3t}^2 + v_t \tag{10}$$

Where v_t is a normally distributed disturbance term independent of ε_t. Note that if $\alpha_1 = ... = \alpha_5 = 0$ in equation (10) the following most hold: $\hat{\varepsilon}_t^2 = \alpha_1 + v_t$. This leads to the following expression: $\hat{\sigma}^2 = \frac{\sum \hat{\varepsilon}_t^2}{N-K} = \frac{\sum(\alpha_1 + \varepsilon_t)}{N-K} = \frac{\alpha_1 N}{N-K}$ since $\sum \alpha_1 = N\alpha_1$, α_1 is a constant and $\sum \varepsilon_t = 0$. This tells us that the variances of the residuals are constant if all the slope coefficients in equation (10) are equal to zero. In this case we have homoscedastic residuals, the opposite holds if the slope coefficients are not equal to zero and then we have heteroscedastic residuals.

White also describes this method as an overall test for model misspecification. The reason is that the null hypothesis of the underlying test assumes a correct linear specification of the model and also that the errors are both homoscedastic and independent of the regressors. If any one of these conditions are violated it could lead to a significant test statistic. On the other hand, a non-significant test statistic implies a correctly specified model.

2.5.2 Autocorrelation

Autocorrelation describe the correlation between residuals at different intervals. E.g. The k:th order autocorrelation of the time series $Y_t \quad t \in [1,.....,T]$ describes the correlation between Y_t and Y_{t-k} (k > 0) i.e. the first order autocorrelation is the correlation between the residual and the residual that is lagged one period. To be able to determine whether autocorrelation is present we use the LM-test (*Lagrange multiplier*) that is an alternative to the Q-statistic for testing autocorrelation. The reason why we use the LM-test is that it will take in order tests for higher order ARMA (*autoregressive moving average*) errors and is appropriate whether or not there are lagged dependent variables. The null hypothesis for the LM test is that there is no autocorrelation up to the k:th lag order. Below we illustrate how the test is carried out.

Assume that we are interested in the following simple model:

$$y_t = \beta_1 + \beta_2 x_t + \varepsilon_t \tag{11}$$

Where ε_t assumingly can be descried with an AR(1)-model.

$$\varepsilon_t = \rho\varepsilon_{t-1} + u_t \tag{12}$$

Next (12) is substituted into equation (11). This gives us the auxiliary regression that we can use to test if k:th order autocorrelation exists: $y_t = \beta_1 + \beta_2 x_t + \rho\varepsilon_{t-1} + u_t$. The LM-test implies that we estimate the original model with OLS and save the residual $\hat{\varepsilon}_t$. After that we substitute ε_{t-1} in the equation above for $\hat{\varepsilon}_{t-1}$, which gives us the following model:

$$y_t = \beta_1 + \beta_2 x_t + \rho\hat{\varepsilon}_{t-1} + u_t \tag{13}$$

This is our auxiliary model which can be estimated with OLS. Now we can test the null hypothesis that the residual in equation (11) is not serially correlated against that it is autocorrelated. See Westerlund (2005), for further discussion and details.

Presence of autocorrelation has the same consequences for the OLS estimator as the case with heteroscedasticity: the OLS-estimator is no longer BLUE, i.e. hypothesis testing is no longer reliable. Fortunately, the Newey-West variance-covariance estimator can remedy this problem.

2.5.3 The Newey-West estimator

The Newey-West estimator is similar to White's heteroscedasticity consistent estimator but differs in the sense that it also makes adjustments for serial correlation.
The Newey-West estimator in matrix notation:

$$Cov(\mathbf{b}) = N(\mathbf{x}'\mathbf{x})^{-1}\mathbf{s}(\mathbf{x}'\mathbf{x})^{-1} \qquad (14)$$

To be able to calculate the variance-covariance matrix in equation (14) we have to substitute the residual ε_t with the OLS-residual $\hat{\varepsilon}_t$. The estimator in equation (14) is both heteroscedasticity and autocorrelation consistent, therefore we can say that Newey-West estimator is a robust estimator. See Westerlund (2005), for further discussion and details.

2.5.4 Multicollinearity

The problem with multicollinearity can emerge when we estimate models with several explanatory variables. This problem comes from high correlation between two or more of the independent variables; they have a systematic dependency which leads to spurious regressions. A rule of thumb says that if the correlation coefficient is above 0,8 action has to be taken, e.g. by excluding one of the highly correlated variables and re-estimating the model. However one should be careful with excluding too many variables, as it could result in a misleading model. See Westerlund (2005), for further discussion and details.

3. METHOD

In this chapter we aim to clarify the empirical method used throughout this thesis. We will provide a basic description of the way this study is performed and specify the empirical models employed. Furthermore, we will discuss our data collection procedure and describe how factors have been constructed.

3.1 MOTIVATION

Within this thesis we use empirical material consisting of authentic observations to test our particular hypothesis. Therefore the thesis has a deductive approach i.e. we present a problem which is tested under several hypotheses (Halvorsen [1992]). The expectation is that we, through our hypotheses, will be able to prove real events. The quantitative character of this thesis makes deductive approach seem logical for purpose of testing if Swedish hedge funds deliver abnormal returns.

3.2 GENERAL METHOD OF WORK

First we collected data material from Reuters, the data contains monthly observations during the time period 2004-02-01 to 2007-01-01. This gives us 36 observations each for the 16 individual hedge funds. Then we calculated the excess returns over the Swedish risk free rate for each of the hedge funds. The returns sensitivity against several explaining variables is estimated with OLS, the regression estimations are performed under three models, CAPM, Fama-French three-factor model and a conditional six-factor model. For each model we test for autocorrelation and heteroscedasticity. We re-estimate the models with the Newey-West robust estimator to account for these properties. Important tests and results are summarized and presented in tables throughout the thesis and in the appendix.

3.3 DATA

This study uses primary data from three main sources, the Reuters database, the Datastream database and Professor Kenneth R. French. Professor French is a recognized researcher in the field of finance with plenty of published articles on his behalf, for example “The Cross-Section of Expected Stock Returns” from 1992 where he in collaboration with Eugene F. Fama first proposed the Fama-French three-factor model. In cases where only price-series has been available the data has been transformed into returns using the natural logarithm:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{15}$$

The hedge fund returns are defined accordingly as the natural logarithm of the funds' net asset value at the end of a month over the net asset value in the beginning of the month:

$$r_t = \ln\left(\frac{NAV_t}{NAV_{t-1}}\right) \tag{16}$$

Net asset value is net of incentive fees which are annual[4].

Monthly data during the period February 2004 to January 2007 is used giving us a total of 36 observations for each time-series. Monthly data has some strong advantages over annual, greatly enhancing the accuracy of the standard deviation measure of risk. Furthermore, apart from giving us more observations, hedge fund return fluctuations can be tracked more closely, as opposed to annual data were these fluctuations tend to be smoothed.

[4] The funds send return data to data vendors after these fees has been allocated over the months using various methods.

- $\mathbf{r_i}$ is the return on 16 Swedish hedge funds. The data is collected from Reuters. The following hedge funds are included:

Fund	**Strategy**
Aktie-Ansvar Graal	Hedge/Multi Strategies
Banco Hedge	Hedge/Equity Market Neutral
Bid & Ask Stella Nova Hedgefond	Hedge/Multi Strategies
Cicero Hedge	Hedge/Long/Short Equity
Coeli Horisont	Hedge/Multi Strategies
DnB NOR Aktiehedgefond Primus	Hedge/Long/Short Equity
DnB NOR ARI Prisma	Hedge/Multi Strategies
Erik Penser Hedgefond	Hedge/Long/Short Equity
Guide Hedgefond	Hedge/Long/Short Equity
H&Q Global Hedge	Hedge/Multi Strategies
H&Q Nordic Hedge	Hedge/Multi Strategies
H&Q Solid	Hedge/Multi Strategies
Handelsbanken`s Hedgefond Aktie	Hedge/Long/Short Equity
Libra	Hedge/Long/Short Equity
Nordea European Equity Hedge Fund	Hedge/Equity Market Neutral
SEB Multihedge	Hedge/Multi Strategies

Table 3.1 Included hedge funds and their associated strategies

- $\mathbf{r_m}$ is the return on OMXS30 which is used as proxy for the market. The data is collected from Reuters.

- $\mathbf{r_f}$ is the return on a Swedish 30-day Treasury-bill (SSVX). The data is collected from Reuters

- **SMB** is a Fama-French factor constructed by forming six value-weighted portfolios on size and book-to-market. SMB is the average return on the three small portfolios minus the average return on the three big portfolios:
  SMB = 1/3(Small Value + Small Neutral + Small Growth) – 1/3(Big Value + Big Neutral + Big Growth)
  The data is collected from the homepage of Kenneth R. French.

- **HML** is a Fama-French factor constructed by forming six value-weighted portfolios on size and book-to-market. HML is the average return on the two value portfolios minus the average return on the two growth portfolios:
  HML = 1/2(Small Value + Big Value) – 1/2(Small Growth + Big Growth)
  The data is collected from the homepage of Kenneth R. French.

- **TERM** is the monthly return on a long-term government bond portfolio minus the 1-month lagged 30-day Treasury bill return. A Datastream index[5] is used as a proxy for the long-term government bond portfolio and the Swedish SSVX as the treasury-bill return. Data is collected from Reuters and Datastream.

- **JPGBI** is the return on the JP Morgan Global Bond Index. Data is collected from Reuters.

- **MT** is the maximum of the excess market return and zero following Henriksson & Merton (1981). Data on market return is collected from Reuters.

- **GDP** is the Swedish gross domestic product. Data is collected from Reuters.

- **TCW** is an index consisting of a basket of currencies relative to the Swedish krona (SEK). Data is collected from Reuters.

3.3.1 Potential biases

According to Edwards & Caglayan (2001) estimating excess returns on hedge funds are potentially subject to a number of data biases associated with reported hedge fund returns. Following previous literature, for instance Fung & Hsieh (2000), four biases are discussed: survivorship bias, instant history bias, selection bias and a multi-period sampling bias.
A survivorship bias might be present if non-surviving funds are excluded from the sample. To explain this bias we distinguish between surviving funds and defunct funds. Surviving funds are still operating and report return data as opposed to defunct funds that has stopped their reporting for various reasons. These might be bankruptcies, liquidations, mergers, name change or

[5] Sweden Total Over 10 Years Datastream Government Index

voluntary stoppage of reporting. If the main reason for defunct is poor performance the returns of the reported sample will be biased upwards. Fung & Hsieh (2000) estimated the survivorship bias to 3% annually from 1994 to 1998 whereas Edwards & Caglayan estimated it to be between 0, 36% and 3, 06% depending on strategy in their 2001 article.

An instant history bias potentially exists, due to the fact that when data vendors add a new hedge fund to their records, historical returns may be back filled. The rationale behind this bias is that only funds with good instant history track records are interested in starting to report their returns. Edwards & Caglayan (2001) estimates this bias to about 1% of annual hedge fund returns.

There might be a selection bias present if only funds with good performance choose to report their returns. In this case the returns of the observable hedge funds will overstate the true returns on the entire population of hedge funds. In contrast, Edwards & Caglayan (2001) report that anecdotal evidence point out the fact that very successful funds choose not to disclose their performance as they are already closed to new investors. If this is the dominating force it will lead to a downward bias in returns. In conclusion, this bias may be either upwards or downwards. In either case Fung & Hsieh (2000) argue that the bias should be very small, if it exists at all.

The last bias, multi-period sampling bias, deals with a requirement that a fund needs a sufficient return history before it can be included as a sample in a study. Fung & Hsieh (2000) argue that if investors typically require 36 months of return history before investing in a fund, estimates of returns based on shorter time-periods might be misleading to those investors. However, the authors concluded that this bias appears to be very small if it exists at all. Fung & Hsieh (1997a) required a 36-month return history to ensure sufficient degrees of freedom in their regressions. Edwards & Caglayan (2001) settles for 24-months. Both articles mentioned above agree that this bias appears to be very small. Ackermann et Al. (1999) also required 24 months.

Due to a very limited number of hedge funds with domicile in Sweden and a sufficient return history, we have made no attempt to adjust our data sample to account for these biases. Nevertheless, we are fully aware of the potential impact from especially the survivorship bias and the instant history bias. Consequently we will consider these biases when we interpret the results from our regressions.

3.4 THE REGRESSION MODELS

Based on the empirical material, consisting of return data on 16 Swedish hedge funds, we attempt to evaluate the performance of these funds. In order to do so we will estimate alpha-values from three different asset pricing models. To be able to draw correct inferences from the regression models it is imperative to test the data for autocorrelation and heteroscedasticity. As described in chapters 2.3.1 and 2.3.2 we will employ the White test for heteroscedasticity and Breusch-Godfrey Lagrange Multiplier (LM) test for serial correlation. The robust variance-covariance estimator of Newey-West will be employed to correct the associated standard errors. This procedure will allow us to draw correct inferences about coefficients and alpha-values. An alpha-value significantly different from zero implies that the model at hand cannot fully explain the return generated by the hedge fund. This might be due to a miss-specified model which lacks relevant explanatory variables, another explanation is directly related to the fund managers' ability to manage the fund. Under the assumption of correctly specified models the alpha will be a measure of hedge fund performance linked to the skill of the manager.

3.4.1 CAPM

The first model we will test is the Capital Asset Pricing Model which is based on the assumption that an asset's return can fully be explained by the asset exposure to the market portfolio. In theory the market portfolio consists of all assets in the economy, in practice such portfolio is impossible to construct. Since this study focus on Swedish hedge funds we will use the OMXS30 index as a proxy for the market portfolio. The risk free rate of return is per definition completely without risk. However, in reality such an asset does not exist, it is common to instead employ a short-term fixed-income instrument issued by a highly credit-worthy government. We use the interest rate on a 30-day Swedish treasury-bill as a proxy for the risk free rate of return.

The model used to test whether the funds generate abnormal returns under the CAPM is the following:

$$r_{it} - r_{ft} = \alpha_i + \beta_i \left(r_{mt} - r_{ft} \right) + \varepsilon_t \tag{17}$$

3.4.2 Fama-French three-factor model

The Fama-French three factor model is an extension of the CAPM, the additional factors are created by forming two portfolios. One is long in small (i.e. low market capitalization) firms and short in large firms (SMB) and the other is long in value stocks (i.e. high book-to-market) and short in growth stocks. These portfolios may be regarded as proxies for non-diversifiable risk factors. The model below is used to test for abnormal returns under the Fama-French three factor model.

$$r_{it} - r_{ft} = \alpha_i + \beta_{i1}\left(r_{mt} - r_{ft}\right) + \beta_{i2}SMB + \beta_{i3}HML + \varepsilon_t \qquad (18)$$

r_{mt} and r_{ft} are the same as in 3.4.1.

3.4.3 Conditional six-factor model

We created a six-factor model (see chapter 2.1.3) by building upon the three factor model by Fama and French. The added factors are supposed to account for market risk in bond returns due to unexpected interest rate changes (TERM), exposure to the bond market (JPGBI) and market-timing ability (MT).

By combining our six-factor asset pricing model with the conditional approach of Ferson & Harvey (1999) we end up with the following econometric model to test for abnormal performance:

$$\begin{aligned} r_{it} - r_{ft} &= \alpha_{i0} + \alpha_{i1} z_t + \beta_{i1}(r_{mt} - r_f) + \beta_{i2}(SMB) + \beta_{i3}(HML) + \beta_{i4}(TERM) + \\ &+ \beta_{i5}(JPGBI) + \beta_{i6}(MT) + \beta_p^{'}[z_t(r_{mt} - r_f)] + \beta_p^{'}(z_t \cdot SMB) + \\ &+ \beta_p^{'}(z_t \cdot HML) + \beta_p^{'}(z_t \cdot TERM) + \beta_p^{'}(z_t \cdot JPGBI) + \beta_p^{'}(z_t \cdot MT) + \varepsilon_t \end{aligned} \qquad (19)$$

The extended form of the model is:

$$
\begin{aligned}
r_{it} - r_{ft} &= \alpha_{i0} + \alpha_{i1} z_t + \beta_{i1}(r_{mt} - r_f) + \beta_{i2}(SMB) + \beta_{i3}(HML) + \beta_{i4}(TERM) + \\
&+ \beta_{i5}(JPGBI) + \beta_{i6}(MT) + \beta_{i7}[GDP(r_{mt} - r_f)] + \beta_{i8}[TCW(r_{mt} - r_f)] + \\
&+ \beta_{i9}(GDP \cdot SMB) + \beta_{i10}(TCW \cdot SMB) + \beta_{i11}(GDP \cdot HML) + \\
&+ \beta_{i11}(TCW \cdot HML) + \beta_{i12}(GDP \cdot TERM) + \beta_{i13}(TCW \cdot TERM) + \\
&+ \beta_{i14}(GDP \cdot JPGBI) + \beta_{i15}(TCW \cdot JPGBI) + \beta_{i16}(GDP \cdot MT) + \\
&+ \beta_{i17}(TCW \cdot MT),
\end{aligned}
\tag{20}
$$

The instrumental variables employed are supposed to be proxies for business-cycles; more specifically we use the Swedish gross domestic product (GDP) and the fluctuations of the Swedish exchange rate against other currencies (TCW). r_{mt} and r_{ft} are the same as in 3.4.1. In accordance SMB and HML follow the definition in 3.4.2.

4. RESULTS AND DISCUSSION

In this chapter we will present the estimates from our regression models. At first we will take a look on some descriptive statistics which is followed by tests and regressions on the hedge fund returns. The results will be presented and discussed under each model respectively.

4.1 DESCRIPTIVE STATISTICS

In table 4.1 we present descriptive statistics for the data material used in this thesis. One very interesting statistic is the Sharpe ratio, it calculates the ratio of the mean excess return over the risk free rate and the variance. In other words it is a statistic measure of how much return one unit of risk (standard deviation) generates. The hedge funds that turns out to be ranked highest according to this measure is *Bid & Ask Stella Nova Hedgefond* and *Erik Penser Hedgefond,* on the opposite of the ranking scale we see that *Cicero Hedge* and *SEB Multihedge* has a negative ratios which means that they have expected returns that are lower than the risk free rate of return. As a comparison we can look at the Sharpe ratio for the OMXS30 index during the same time-period which equals 0,381, this is in fact higher than for all the funds. The conclusion to be drawn from this performance measure is that an investor having a quadratic utility function or mean-variance preferences should always chose to invest in the index over any of the hedge funds. The Jarque-Bera measure is a test to determine if a time-series follows a normal distribution, the test itself, examines if the skewness and kurtosis of the data residuals is similar to the normally distributed residuals. The JB test statistic asymptotically follows a chi-two distribution with two degrees of freedom under the null hypothesis: JB ~ $\chi^2_{(2)}$.

On the 5 % significance level J-B has a critical value ≈ 5, 99. If the JB statistic exceeds the critical value we can reject the null hypothesis and state that residuals are not normally distributed. If the JB statistic is close to zero on the other hand, we cannot reject the null and therefore the residuals are considered to be normally distributed (Westerlund, [2005]).

As is evident from table 4.1 below, all JB statistics are below the critical value and hence the p-values are above 5 %, this suggests that we cannot reject the null for any of the hedge funds.

The monthly mean returns of the hedge funds range from 0,073% to 0,867% with a mean of 0,476% .

Fund	Mean	Variance	Sharpe	Skewness	Kurtosis	JB	P
Aktie-Ansvar Graal	0,576%	0,071%	0,154	-0,063	-1,157	2,057	0,358
Banco Hedge	0,415%	0,091%	0,083	-0,032	-0,955	1,474	0,479
Bid & Ask Stella Nova Hedgefond	0,781%	0,064%	0,244	-0,083	-1,214	2,249	0,325
Cicero Hedge	0,137%	0,081%	-0,010	-0,036	-0,944	1,449	0,485
Coeli Horisont	0,596%	0,069%	0,163	0,285	-0,879	1,729	0,421
DnB NOR Aktiehedgefond Primus	0,597%	0,104%	0,134	0,134	-0,609	0,725	0,696
DnB NOR ARI Prisma	0,640%	0,093%	0,156	0,079	-1,068	1,807	0,405
Erik Penser Hedgefond	0,867%	0,084%	0,242	0,293	-0,990	2,031	0,362
Guide Hedgefond	0,449%	0,075%	0,104	0,446	-0,857	2,323	0,313
H&Q Global Hedge	0,308%	0,102%	0,044	0,125	-1,082	1,898	0,387
H&Q Nordic Hedge	0,544%	0,078%	0,136	0,045	-0,769	1,041	0,594
H&Q Solid	0,579%	0,095%	0,134	0,040	-1,006	1,611	0,447
Handelsbanken`s Hedgefond Aktie	0,325%	0,081%	0,056	-0,138	-1,188	2,234	0,327
Libra	0,272%	0,089%	0,036	0,193	-1,356	2,888	0,236
Nordea European Equity Hedge Fund	0,460%	0,072%	0,110	-0,160	-0,931	1,549	0,460
SEB Multihedge	0,073%	0,120%	-0,027	-0,855	1,372	5,603	0,061

Table 4.1 Descriptive statistics. Note that kurtosis is reported as excess over the normal distribution.

Table 4.2 gives an account of correlations among factors and instruments. With the noticeable exceptions of SMB and MT and not surprisingly TERM and JPGBI correlations are small suggesting that multicollinearity should not be a problem.

	MKTRF	SMB	HML	JPGBI	TERM	MT	GDP	TCW
MKTRF	1							
SMB	0,347	1						
HML	-0,252	-0,258	1					
JPGBI	0,155	0,117	-0,063	1				
TERM	-0,030	0,088	0,050	0,702	1			
MT	0,404	0,726	-0,282	0,070	0,208	1		
GDP	0,101	-0,032	0,030	-0,235	-0,279	0,009	1	
TCW	0,019	0,046	-0,216	-0,098	-0,301	-0,121	0,041	1

Table 4.2 Correlation between factors and instruments

4.2 CAPM

We start out with estimating Jensen's alpha under the market model (CAPM) to determine whether we can see any evidence of abnormal performance. The CAPM is estimated according to the econometric model (9) from chapter 3.4.1:

$$r_{it} - r_{ft} = \alpha_i + \beta_i \left(r_{mt} - r_{ft} \right) + \varepsilon_t$$

4.2.1 Heteroscedasticity and autocorrelation tests on CAPM

CAPM	Heteroscedasticity		Autocorrelation	
Fund	F-statistic	P-value	F-statistic	P-value
Aktie-Ansvar Graal	0,76	0,48	1,96	0,13
Banco Hedge	0,74	0,49	2,44	0,07*
Bid & Ask Stella Nova Hedgefond	0,69	0,51	2,09	0,11
Cicero Hedge	1,00	0,38	1,60	0,20
Coeli Horisont	0,28	0,76	2,14	0,10
DnB NOR Aktiehedgefond Primus	0,12	0,89	0,70	0,60
DnB NOR ARI Prisma	0,17	0,84	1,66	0,19
Erik Penser Hedgefond	1,36	0,27	1,49	0,23
Guide Hedgefond	0,92	0,41	1,66	0,19
H&Q Global Hedge	0,99	0,38	1,90	0,14
H&Q Nordic Hedge	0,62	0,55	1,18	0,34
H&Q Solid	0,82	0,45	2,14	0,10
Handelsbanken`s Hedgefond Aktie	0,25	0,78	1,21	0,33
Libra	0,37	0,70	2,66	0,05*
Nordea European Equity Hedge Fund	2,05	0,14	2,24	0,09*
SEB Multihedge	0,43	0,65	0,73	0,58

Table 4.3 The Heteroscedasticity and autocorrelation tests on CAPM.
**Significant at the 10% level. ** Significant at the 5% level. ***Significant at the 1% level.*

The result from the serial correlation and heteroscedasticity tests is presented in table 4.3. We find no evidence of heteroscedasticity for either of the funds under CAPM. Only three funds (*Banco Hedge, Libra and Nordea European Equity Hedge Fund*) show evidence of autocorrelation, on a 10% level, for the rest of the funds we cannot reject the null hypothesis of no autocorrelation.

4.2.2 Regression under CAPM

The estimated coefficients and associated p-values from the CAPM-regressions are offered in table 4.4. Only one fund, *Bid & Ask Stella Nova Hedgefond*, has a significant alpha on the 10% level whereas all the other funds' alphas are insignificant. Two of the funds display a statistical significant loading with the market, on the 10 % level *Erik Penser Hedgefond* and on the 1 % level *Banco Hedge.* Both these funds have a positive beta coefficient implying that they are long in Swedish equity.

Fund	α	P	β_{rm-rf}	P	R^2	Adj. R^2
Aktie-Ansvar Graal	0,005	0,32	-0,034	0,64	0,2%	-2,7%
Banco Hedge	-0,001	0,82	0,268	0,00***	10,3%	7,7%
Bid & Ask Stella Nova Hedgefond	0,007	0,09*	-0,036	0,57	0,3%	-2,7%
Cicero Hedge	0,000	0,94	0,002	0,97	0,0%	-2,9%
Coeli Horisont	0,004	0,43	0,054	0,43	0,6%	-2,4%
DnB NOR Aktiehedgefond Primus	0,003	0,58	0,078	0,33	0,8%	-2,1%
DnB NOR ARI Prisma	0,004	0,42	0,034	0,66	0,2%	-2,8%
Erik Penser Hedgefond	0,005	0,21	0,134	0,07*	2,8%	-0,1%
Guide Hedgefond	0,003	0,59	0,016	0,81	0,0%	-2,9%
H&Q Global Hedge	0,001	0,85	0,025	0,74	0,1%	-2,9%
H&Q Nordic Hedge	0,004	0,46	0,007	0,93	0,0%	-2,9%
H&Q Solid	0,003	0,54	0,055	0,43	0,4%	-2,5%
Handelsbanken`s Hedgefond Aktie	0,001	0,82	0,042	0,64	0,3%	-2,7%
Libra	0,001	0,78	-0,017	0,85	0,0%	-2,9%
Nordea European Equity Hedge Fund	0,002	0,63	0,066	0,29	0,8%	-2,1%
SEB Multihedge	0,000	0,95	-0,041	0,69	0,2%	-2,7%

Table 4.4 The Regressions on CAPM.
**Significant at the 10% level. ** Significant at the 5% level. ***Significant at the 1% level.*

4.2.3 Discussion on the CAPM model results

The first thing we notice is that the explanatory power of the model, measured by R^2, is very poor ranging from 0 to 10,3 %. This indicates low general correlation between hedge funds and the equity asset class, represented by the OMXS30 index. It is somewhat surprising that *Banco Hedge* exhibits a positive strongly significant factor loading with the market since the fund follows a market neutral strategy. *Erik Penser Hedge* on the other hand uses a long/short equity strategy why the significant factor loading might be expected. The positive beta informs us that the fund, on average, has been long in Swedish equity during the period February 2004 to

January 2007. Another thing that strikes us is that several funds in the sample have equity based strategies, but that is for some reason not reflected in the estimated regression coefficients. A plausible explanation for this has to do with the model specification. By construction, betas from the regression were assumed to be constant for 36 months, however, this assumption conflicts with the dynamic trading strategies employed by most hedge funds. If a fund, for example, invested heavily in equities for 18 months and sold the same equities short the following 18 months, the factor loading from a regression would be close to zero.

The alphas, or unexplained returns, ranged from -0, 1% to 0, 7% with an average return of 0, 25%. 15 out of the 16 funds exhibit positive unexplained returns but only one is significant. However, due to lack in explanatory power, the explanatory variable does a poor job in explaining the variations in the dependent variable, we cannot place much confidence in the estimated coefficients and intercepts.

4.3 FAMA-FRENCH THREE-FACTOR MODEL

The next model to test is the Fama-French three-factor model which is an extension of the capital asset pricing model. The model includes a size factor and a book-to-market factor and has been proven to outperform the market model in previous studies. The three-factor model is estimated according to the econometric model in equation (9) from chapter 3.4.1:

$$r_{it} - r_{ft} = \alpha_i + \beta_{i1}\left(r_{mt} - r_{ft}\right) + \beta_{i2}SMB + \beta_{i3}HML + \varepsilon_t$$

4.3.1 Heteroscedasticity and autocorrelation tests on the Fama-French three-factor model

FF 3-factor model	Heteroscedasticity		Autocorrelation	
Fund	F-statistic	P-value	F-statistic	P-value
Aktie-Ansvar Graal	1,02	0,45	1,23	0,32
Banco Hedge	0,99	0,47	3,26	0,03**
Bid & Ask Stella Nova Hedgefond	1,14	0,37	1,58	0,21
Cicero Hedge	0,79	0,63	2,10	0,11
Coeli Horisont	0,91	0,53	1,45	0,25
DnB NOR Aktiehedgefond Primus	1,29	0,29	0,38	0,82
DnB NOR ARI Prisma	0,71	0,70	0,80	0,54
Erik Penser Hedgefond	0,78	0,63	1,68	0,18
Guide Hedgefond	0,79	0,63	1,12	0,37
H&Q Global Hedge	0,50	0,86	0,89	0,48
H&Q Nordic Hedge	0,84	0,59	0,67	0,62
H&Q Solid	0,82	0,61	1,13	0,36
Handelsbanken`s Hedgefond Aktie	1,11	0,39	0,57	0,68
Libra	0,86	0,57	2,25	0,09*
Nordea European Equity Hedge Fund	0,72	0,69	2,60	0,06*
SEB Multihedge	0,69	0,71	0,65	0,63

Table 4.5 The Heteroscedasticity and autocorrelation tests on Fama-French three-factor model.
**Significant at the 10% level. ** Significant at the 5% level. ***Significant at the 1% level.*

The result from the serial correlation and heteroscedasticity tests is presented in table 4.5. We find no evidence of heteroscedasticity for either of the funds under the three-factor model. No more than three funds (*Banco Hedge, Libra and Nordea European Equity Hedge Fund*) show evidence of serial correlation, as for the rest of the funds we cannot reject the null hypothesis of no autocorrelation.

4.3.2 Regression under Fama-French three-factor model

The estimated coefficients/intercept and associated p-values from the Fama-French regressions are presented in table 4.6. None of the alphas are significant, the market factor coefficients are significant for merely two funds; *Banco Hedge* on the 1% level and *Erik Penser Hedgefond* on the 10% level. The size factor is not significant for any of the funds. The estimated HML coefficients give that *Coeli Horisont, DnB NOR ARI Prisma* and *Guide Hedgefond* are significant on the 5% level. *Aktie-Ansvar Graal, Erik Penser Hedgefond, H&Q Global Hedge, H&Q Nordic Hedge, H&Q Solid, Handelsbanken`s Hedgefond Aktie* and *Nordea European Equity Hedge Fund* are significant on the 10% level.

Fund	α	P	β_{rm-rf}	P	β_{SMB}	P	β_{HML}	P	R^2	Adj. R^2
Aktie-Ansvar Graal	0,000	0,97	-0,002	0,98	0,148	0,55	0,576	0,04**	11,2%	2,8%
Banco Hedge	-0,005	0,41	0,280	0,00***	0,169	0,57	0,444	0,11	15,8%	7,9%
Bid & Ask Stella Nova Hedgefond	0,004	0,40	-0,010	0,88	0,061	0,80	0,349	0,25	4,6%	-4,3%
Cicero Hedge	-0,003	0,55	-0,008	0,92	0,221	0,46	0,338	0,30	4,9%	-4,0%
Coeli Horisont	-0,001	0,90	0,079	0,37	0,145	0,55	0,505	0,07*	9,3%	0,8%
DnB NOR Aktiehedgefond Primus	-0,001	0,85	0,099	0,28	0,175	0,59	0,529	0,17	7,4%	-1,3%
DnB NOR ARI Prisma	-0,001	0,91	0,071	0,48	0,131	0,61	0,590	0,06*	8,8%	0,2%
Erik Penser Hedgefond	0,000	0,94	0,146	0,06*	0,299	0,22	0,696	0,02**	18,1%	10,4%
Guide Hedgefond	-0,002	0,68	0,042	0,63	0,178	0,46	0,580	0,05*	10,8%	2,4%
H&Q Global Hedge	-0,006	0,33	0,054	0,54	0,300	0,25	0,848	0,01***	17,5%	9,8%
H&Q Nordic Hedge	-0,001	0,86	0,019	0,85	0,246	0,34	0,592	0,03**	11,8%	3,6%
H&Q Solid	-0,003	0,64	0,089	0,24	0,226	0,41	0,750	0,01**	14,6%	6,6%
Handelsbanken`s Hedgefond Aktie	-0,005	0,38	0,086	0,48	0,134	0,57	0,663	0,03**	12,7%	4,5%
Libra	-0,003	0,54	-0,011	0,92	0,246	0,29	0,534	0,13	8,8%	0,3%
Nordea European Equity Hedge Fund	-0,003	0,51	0,090	0,23	0,214	0,39	0,635	0,04**	14,6%	6,6%
SEB Multihedge	-0,004	0,52	-0,005	0,95	0,067	0,85	0,458	0,21	4,2%	-4,8%

Table 4.6 The Regressions on Fama-French three-factor model.
**Significant at the 10% level. ** Significant at the 5% level. ***Significant at the 1% level.*

4.3.3 Discussion on the Fama-French three-factor model results

The explanatory power of this model has risen in comparison with the market model, but it is still quite poor ranging from 4, 2% to 18, 1%. This suggests that the Fama-French model is not very good at explaining the hedge fund returns and hence other factors are required to capture their variations. In appendix C the explanatory power of a conditional version of this three-factor model is reproduced, indicating that accounting for time-variability substantially increases the goodness of fit.

The unexplained returns, measured by alpha, ranges from -0, 6% to 0, 4%, with an average return of -0, 2%. None of these unexplained returns are significant. In accordance with the result from the CAPM model *Banco Hedge* and *Erik Penser Hedge* display positive significant factor loadings with the market which is to be expected. All of the funds have positive exposure to the size factor, albeit none is statistically significant. Likewise all of the funds have positive factor loadings with HML, but in this case a majority is significant which suggests that HML contributes with more explanatory power than SMB does. This result indicates that hedge fund managers prefer stocks with high book-to-market ratios and those of small firms.

4.4 SIX-FACTOR MODEL

In order to better capture the hedge funds' risk exposure we now extend the Fama-French three-factor model with three additional factors (TERM, JPGBI and MT), by also adding two information variables (GDP and TCW) we end up with a time-varying six-factor model. The model that we will estimate is presented below, for further details se chapter 3.4.3 equation (11).

$$
\begin{aligned}
r_{it} - r_{ft} &= \alpha_{i0} + \alpha_{i1} z_t + \beta_{i1}(r_{mt} - r_f) + \beta_{i2}(SMB) + \beta_{i3}(HML) + \beta_{i4}(TERM) + \\
&+ \beta_{i5}(JPGBI) + \beta_{i6}(MT) + \beta_p^{'}[z_t(r_{mt} - r_f)] + \beta_p^{'}(z_t \cdot SMB) + \\
&+ \beta_p^{'}(z_t \cdot HML) + \beta_p^{'}(z_t \cdot TERM) + \beta_p^{'}(z_t \cdot JPGBI) + \beta_p^{'}(z_t \cdot MT) + \varepsilon_t
\end{aligned}
$$

4.4.1 Heteroscedasticity and autocorrelation tests on six-factor model

Below follows the results from heteroscedasticity and autocorrelation tests under the six-factor model.

Cond. 6-factor model	Heteroscedasticity		Autocorrelation	
Fund	F-statistic	P-value	F-statistic	P-value
Aktie-Ansvar Graal	2,25	0,12	0,83	0,52
Banco Hedge	1,30	0,37	0,44	0,78
Bid & Ask Stella Nova Hedgefond	2,46	0,09*	0,68	0,61
Cicero Hedge	3,93	0,02**	0,87	0,50
Coeli Horisont	1,24	0,40	0,85	0,51
DnB NOR Aktiehedgefond Primus	0,89	0,62	0,73	0,58
DnB NOR ARI Prisma	1,83	0,19	1,04	0,41
Erik Penser Hedgefond	1,30	0,37	0,88	0,49
Guide Hedgefond	0,62	0,83	1,41	0,26
H&Q Global Hedge	1,81	0,19	0,62	0,65
H&Q Nordic Hedge	0,98	0,56	0,62	0,65
H&Q Solid	2,02	0,15	0,71	0,59
Handelsbanken`s Hedgefond Aktie	2,25	0,12	0,34	0,85
Libra	1,61	0,25	2,82	0,05**
Nordea European Equity Hedge Fund	2,01	0,15	1,00	0,43
SEB Multihedge	6,04	0,01***	0,30	0,88

Table 4.7 The Heteroscedasticity and autocorrelation tests on the six-factor model.
**Significant at the 10% level. ** Significant at the 5% level. ***Significant at the 1% level.*

White's test indicate that we have heteroscedastic residuals in three cases: on the 1% level *SEB Multihedge*, on the 5% level *Cicero Hedge* and on the 10% level *Bid & Ask Stella Nova Hedgefond*. We have to reject the null hypothesis of no autocorrelation for *Libra* on the 10 % level. We do not find any evidence of serial correlation for the other funds.

4.4.2 Regression under conditional six-factor model

The test results from the regression under our six-factor model can be seen below in table 4.8. Because of the lack of space we have decided to not present the sensitivities to the information variables in this table, instead they are attached in appendix E.

Fund	α	P	β_{rm-rf}	P	β_{SMB}	P	β_{HML}	P	β_{TERM}	P	β_{JPGBI}	P	β_{MT}	P	R^2	Adj. R^2
Aktie-Ansvar Graal	-0,001	0,79	0,188	0,06*	0,140	0,58	0,518	0,03**	1,295	0,00***	-2,384	0,00***	-0,013	0,98	76%	50%
Banco Hedge	-0,003	0,80	0,443	0,00***	0,257	0,51	0,301	0,45	1,282	0,01***	-2,322	0,00***	-0,338	0,62	58%	14%
Bid & Ask Stella Nova Hedgefond	0,003	0,59	0,184	0,07*	0,042	0,86	0,258	0,35	1,297	0,00***	-2,328	0,00***	0,032	0,95	66%	31%
Cicero Hedge	0,002	0,80	0,247	0,02**	0,489	0,17	0,315	0,37	1,273	0,01***	-2,335	0,00***	-0,573	0,35	70%	38%
Coeli Horisont	-0,002	0,79	0,272	0,01***	0,106	0,75	0,418	0,14	1,271	0,00***	-2,290	0,00***	-0,025	0,96	71%	41%
DnB NOR Aktiehedgefond Primus	0,001	0,89	0,363	0,00***	0,408	0,43	0,425	0,16	1,709	0,00***	-3,064	0,00***	-0,418	0,54	73%	44%
DnB NOR ARI Prisma	0,003	0,56	0,355	0,00***	0,280	0,43	0,450	0,05**	1,771	0,00***	-3,127	0,00***	-0,503	0,32	76%	51%
Erik Penser Hedgefond	0,004	0,61	0,355	0,00***	0,519	0,12	0,707	0,10*	1,048	0,01**	-1,877	0,01**	-0,460	0,35	65%	28%
Guide Hedgefond	-0,006	0,37	0,241	0,05**	0,125	0,73	0,580	0,06*	1,182	0,00***	-1,720	0,02**	0,124	0,83	65%	27%
H&Q Global Hedge	-0,003	0,74	0,323	0,00***	0,427	0,21	0,735	0,00***	1,597	0,00***	-2,969	0,00***	-0,360	0,52	75%	49%
H&Q Nordic Hedge	0,002	0,76	0,277	0,04**	0,409	0,20	0,526	0,04**	1,486	0,00***	-2,585	0,00***	-0,472	0,40	71%	40%
H&Q Solid	0,001	0,95	0,356	0,00***	0,359	0,33	0,647	0,01**	1,567	0,00***	-2,888	0,00***	-0,348	0,58	74%	47%
Handelsbanken`s Hedgefond Aktie	-0,003	0,67	0,320	0,00***	0,157	0,63	0,543	0,02**	1,396	0,00***	-2,656	0,00***	-0,212	0,65	78%	55%
Libra	-0,005	0,34	0,176	0,14	0,144	0,56	0,528	0,10*	1,590	0,00***	-2,981	0,00***	0,166	0,73	71%	40%
Nordea European Equity Hedge Fund	-0,004	0,59	0,287	0,00***	0,246	0,42	0,642	0,03**	1,275	0,00***	-2,086	0,00***	-0,104	0,84	71%	40%
SEB Multihedge	0,007	0,33	0,306	0,01***	0,679	0,14	0,374	0,31	1,054	0,06*	-2,032	0,03**	-1,294	0,06*	70%	38%

Table 4.8 The Regressions on the six-factor model.
**Significant at the 10% level. ** Significant at the 5% level. ***Significant at the 1% level.*

When observing alpha from the estimated six-factor model, we note that it is not significant for any hedge fund. The beta coefficients for r_m-r_f are significant for all hedge funds except *Libra*. At the 10% significance level the following hedge funds are represented: *Aktie-Ansvar Graal* and *Bid & Ask Stella Nova Hedgefond.* At the 5 % level *Cicero Hedge*, *Guide Hedgefond* and *H&Q Nordic Hedge* show significance. The rest of the funds are significant at the 1 % level. None of the funds have a statistically significant exposure to SMB. Regarding the HML factor slightly more than half of the funds have significant loadings. The TERM factor is significant at the 1 % level for a great majority of the funds, the exceptions are *Erik Penser Hedgefond* and *SEB Multihedge* which are significant at the 5 % and the 10 % level respectively. The exposure to JPGBI is similar where only *Erik Penser Hedgefond, Guide Hedgefond* and *SEB Multihedge* have a significance level above 1%. The last factor MT is only significant, and that is at the 10 % level, for one hedge fund; *SEB Multihedge.* Furthermore, we note that the explanatory power of this model is considerably higher for this model than for the other two models.

4.4.3 Discussion on the six-factor model results

All of the studied hedge funds have positive loadings on the market factor, of which almost all are statistically significant, this suggests that the funds are long in the Swedish equities. Every one of the funds has positive exposure to the size factor indicating that the fund managers prefer small firms over large. The bulk of the funds have positive significant coefficients on HML, all are positive, indicating a preference towards value stocks. Another interpretation of the loadings on the Fama-French factors is that all the funds have positive exposure to the underlying economic risk factors for which the Fama-French factors are proxies. The betas for the TERM factor display positive significance in all cases; from this we infer a common sensitivity in returns due to an exposure to the market risk in bond returns caused by unexpected interest rate changes. Significantly negative factor loadings on the JP Morgan Global Bond Index are evident for all hedge funds. We take from this fact that all hedge funds use leverage to enhance returns. An alternative interpretation is that hedge funds are long in assets that are negatively correlated with bonds. A majority of the fund managers exhibit negative market timing capabilities, although only one is significant (10%). The market timing factor does not seem to contribute much to the models explanatory power.

The high explanatory power of this model indicates that it is much more competent when it comes to explaining hedge fund returns than the other two models. The average R^2 has risen to 71% whereas the adjusted R^2 is 39% on average. This high goodness of fit statistic makes us much more confident that valid conclusions can be drawn. We have also estimated the regressions with a static version of the six-factor model and concluded that the inclusion of the instruments contribute significantly to the models explanatory power (See appendix D).

5. CONCLUSION

In this chapter, we will summarize the results and draw conclusions regarding them. Finally, we will present potential areas and subjects of interest for further studies.

We have examined whether 16 Swedish hedge funds have been able to deliver abnormal returns during the period February 2004 to January 2007 employing two static and one conditional asset pricing model. As measures of performance we have used the Sharpe ratio and Jensen's alpha, which is the intercept from the estimated factor models. The models we have estimated are the CAPM, the Fama-French three-factor model and a time-varying six-factor model.

Model	Number of significant α	Average α	Average R^2	Average adjusted R^2
CAPM	1	0,003	1,1%	-1,9%
F-F 3-factor	0	-0,002	10,9%	2,6%
Cond. 6-factor	0	0,000	70,7%	39,6%

Table 5.1 Comparison of estimated alphas and goodness of fit between the three models. Alpha is significant if P < 0, 10.

As can be seen in table 5.1 none of the models indicate abnormal performance in the form of significant alphas. In fact, only the market model provides significant alphas at all, in one case, which is on the 10% level for *Bid & Ask Stella Nova Hedgefond*. The obvious conclusion is therefore that no abnormal performance has been evident for any of the funds during the studied period. This result stands in contrast to several previous studies (e.g. Edwards & Caglayan [2001]; Kat & Miffre [2003]; Liang [1999]) but is in line with Ackermann et al. (1999) who found that hedge funds are not able to beat the market net of fees.

In accordance with our expectations the explanatory power of the models increase with the number of included factors and is amplified even further with the usage of time-varying factor loadings. We do not put much trust in the market-model due to its poor goodness of fit, for the same reason we are a bit sceptical about the benefits of the three-factor model. As a consequence of the regression estimates obtained for the three different models, we draw the conclusion that the CAPM and the Fama-French three-factor model are unsuitable for evaluating hedge fund performance. It seems quite obvious to us that traditional static asset pricing models are not capable of capturing the dynamic risk exposure of hedge funds. First of all, new factors are required (e.g. exposure to bonds, commodities etc.) and secondly the ability to account for time-varying factor exposure seem imperative.

Regarding the conditional six-factor model we are quite pleased with an average adjusted R^2 of nearly 40 %, especially since Kat & Miffre (2003) report adjusted goodness of fit of about 35% for a similar model. In the light of the satisfying explanatory power of the time-varying six-factor model we are confident in our conclusion that no abnormal returns have been generated by the studied hedge funds. This belief is further enhanced by the fact that all the hedge funds have lower Sharpe ratios than the OMXS30.

As we mention in chapter 3.3.1 no adjustment for different biases have been made. Making those adjustments would have resulted in even weaker performance, thus giving further support to our conclusion of no positive abnormal returns.

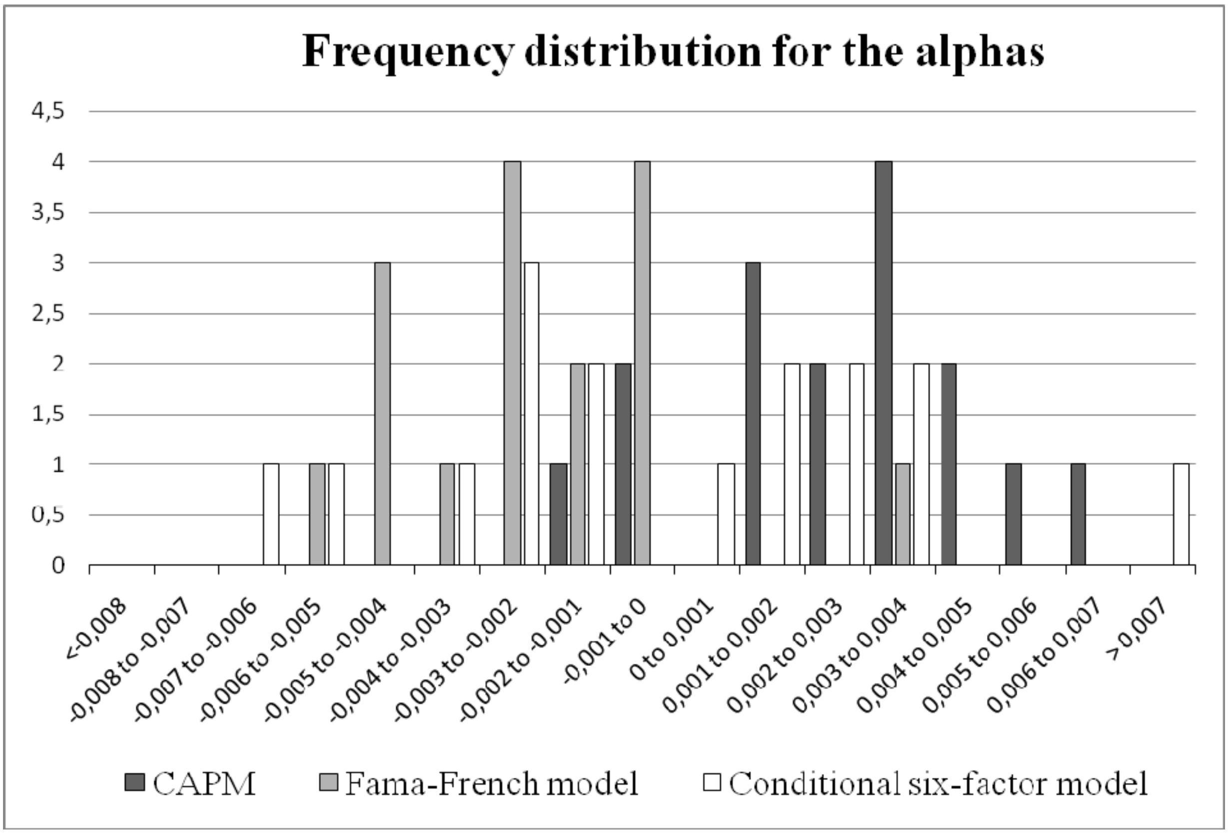

Figure 5.1 Frequency distribution for the alphas grouped by model.

As is evident from the alpha frequency distribution in figure 5.1 above, the alphas are more dispersed in the six-factor model compared to the other two models, assuming that this model is superior to the other two this fact indicates considerable heterogeneity across hedge fund performance.

5.1 FURTHER STUDIES

An interesting continuation of this study would be to add or change both the factors and the instrumental variables to see whether a better model can be constructed. Suggestions of new factors might be indexes on commodities or credit default swaps. Furthermore, a longer study period might be rewarding, especially since there is previous evidence of better hedge fund performance in down-markets and our study was performed during an up-market. A further reason for extending the sample period is that, generally, more observations improve the regression estimates and increase the chance of finding significant alphas.

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2007-02-20

Homepage of Kenneth R. French
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APPENDIX

A. LIST OF FIGURES

B. LIST OF TABLES

C. EXPLANATORY POWER OF CONDITIONAL THREE-FACTOR MODEL

$$r_{it} - r_{ft} = \alpha_{i0} + \alpha_{i1} z_t + \beta_{i1}(r_{mt} - r_f) + \beta_{i2}(SMB) + \beta_{i3}(HML) + \beta_p^{'}[z_t(r_{mt} - r_f)] +$$
$$+ \beta_p^{'}(z_t \cdot SMB) + \beta_p^{'}(z_t \cdot HML) + \varepsilon_t$$

Fund	R^2	Adj. R^2
Aktie-Ansvar Graal	36%	13%
Banco Hedge	26%	1%
Bid & Ask Stella Nova Hedgefond	25%	-1%
Cicero Hedge	28%	4%
Coeli Horisont	31%	7%
DnB NOR Aktiehedgefond Primus	33%	10%
DnB NOR ARI Prisma	29%	4%
Erik Penser Hedgefond	31%	7%
Guide Hedgefond	30%	6%
H&Q Global Hedge	34%	11%
H&Q Nordic Hedge	23%	-3%
H&Q Solid	34%	10%
Handelsbanken`s Hedgefond Aktie	34%	11%
Libra	28%	4%
Nordea European Equity Hedge Fund	33%	9%
SEB Multihedge	36%	14%
Mean	31%	7%
Min	23%	-3%
Max	36%	14%

D. EXPLANATORY POWER OF STATIC SIX-FACTOR MODEL

$$r_{it} - r_{ft} = \alpha_i + \beta_{i1}(r_{mt} - r_f) + \beta_{i2}(SMB) + \beta_{i3}(HML) + \beta_{i4}(TERM) +$$
$$+ \beta_{i5}(JPGBI) + \beta_{i6}(MT) + \varepsilon_t$$

Fund	R^2	Adj. R^2
Aktie-Ansvar Graal	48%	37%
Banco Hedge	38%	25%
Bid & Ask Stella Nova Hedgefond	38%	25%
Cicero Hedge	37%	24%
Coeli Horisont	42%	30%
DnB NOR Aktiehedgefond Primus	43%	31%
DnB NOR ARI Prisma	48%	37%
Erik Penser Hedgefond	40%	27%
Guide Hedgefond	37%	23%
H&Q Global Hedge	49%	38%
H&Q Nordic Hedge	51%	41%
H&Q Solid	48%	38%
Handelsbanken`s Hedgefond Aktie	52%	42%
Libra	42%	30%
Nordea European Equity Hedge Fund	42%	30%
SEB Multihedge	24%	9%
Mean	42%	31%
Min	24%	9%
Max	52%	42%

E. REGRESSION OUTPUT – CONDITIONAL SIX-FACTOR MODEL

Aktie-Ansvar Graal

	α	β	P
C	-0,001		0,79
r_m-r_f		0,188	0,06
SMB		0,140	0,58
HML		0,518	0,03
TERM		1,295	0,00
JPGBI		-2,384	0,00
MT		-0,013	0,98
GDP*r_m		0,000	0,22
TCW*r_m		-0,044	0,74
GDP*SMB		0,000	0,58
TCW*SMB		-0,121	0,08
GDP*HML		0,000	0,18
TCW*HML		0,220	0,01
GDP*TERM		0,000	0,62
TCW*TERM		-0,207	0,05
GDP*JPGBI		0,000	0,30
TCW*JPGBI		0,460	0,03
GDP*MT		0,000	0,74
TCW*MT		0,011	0,92
R^2			76%
Adj. R^2			50%

Banco Hedge

	α	β	P
C	-0,003		0,80
r_m-r_f		0,443	0,00
SMB		0,257	0,51
HML		0,301	0,45
TERM		1,282	0,01
JPGBI		-2,322	0,00
MT		-0,338	0,62
GDP*r_m		0,000	0,53
TCW*r_m		0,108	0,45
GDP*SMB		0,000	0,61
TCW*SMB		0,001	0,99
GDP*HML		0,000	0,70
TCW*HML		0,089	0,49
GDP*TERM		0,000	0,82
TCW*TERM		-0,234	0,04
GDP*JPGBI		0,000	0,47
TCW*JPGBI		0,508	0,09
GDP*MT		0,000	0,43
TCW*MT		-0,170	0,22
R^2			58%
Adj. R^2			14%

Bid & Ask Stella Nova Hedgefond

	α	β	P
C	0,003		0,59
r_m-r_f		0,184	0,07
SMB		0,042	0,86
HML		0,258	0,35
TERM		1,297	0,00
JPGBI		-2,328	0,00
MT		0,032	0,95
GDP*r_m		0,000	0,37
TCW*r_m		-0,115	0,46
GDP*SMB		0,000	0,38
TCW*SMB		-0,116	0,14
GDP*HML		0,000	0,30
TCW*HML		0,225	0,02
GDP*TERM		0,000	0,46
TCW*TERM		-0,197	0,13
GDP*JPGBI		0,000	0,22
TCW*JPGBI		0,477	0,06
GDP*MT		0,000	0,49
TCW*MT		0,092	0,45
R^2			66%
Adj. R^2			31%

Cicero Hedge

	α	β	P
C	0,002		0,80
r_m-r_f		0,247	0,02
SMB		0,489	0,17
HML		0,315	0,37
TERM		1,273	0,01
JPGBI		-2,335	0,00
MT		-0,573	0,35
GDP*r_m		0,000	0,18
TCW*r_m		-0,121	0,41
GDP*SMB		0,000	0,60
TCW*SMB		-0,084	0,34
GDP*HML		0,000	0,12
TCW*HML		0,194	0,03
GDP*TERM		0,000	0,73
TCW*TERM		-0,331	0,02
GDP*JPGBI		0,000	0,63
TCW*JPGBI		0,645	0,01
GDP*MT		0,000	0,53
TCW*MT		0,066	0,63
R^2			70%
Adj. R^2			38%

Coeli Horisont

	α	β	P
C	-0,002		0,79
r_m-r_f		0,272	0,01
SMB		0,106	0,75
HML		0,418	0,14
TERM		1,271	0,00
JPGBI		-2,290	0,00
MT		-0,025	0,96
GDP*r_m		0,000	0,21
TCW*r_m		-0,056	0,67
GDP*SMB		0,000	0,72
TCW*SMB		-0,109	0,13
GDP*HML		0,000	0,28
TCW*HML		0,188	0,05
GDP*TERM		0,000	0,37
TCW*TERM		-0,213	0,03
GDP*JPGBI		0,000	0,20
TCW*JPGBI		0,482	0,01
GDP*MT		0,000	0,51
TCW*MT		0,008	0,94
R^2			71%
Adj. R^2			41%

DnB NOR Aktiehedgefond Primus

	α	β	P
C	0,001		0,89
r_m-r_f		0,363	0,00
SMB		0,408	0,43
HML		0,425	0,16
TERM		1,709	0,00
JPGBI		-3,064	0,00
MT		-0,418	0,54
GDP*r_m		0,000	0,46
TCW*r_m		-0,071	0,55
GDP*SMB		0,000	0,37
TCW*SMB		-0,115	0,32
GDP*HML		0,000	0,03
TCW*HML		0,198	0,04
GDP*TERM		0,000	0,83
TCW*TERM		-0,171	0,17
GDP*JPGBI		0,000	0,45
TCW*JPGBI		0,285	0,13
GDP*MT		0,000	0,72
TCW*MT		0,037	0,78
R^2			73%
Adj. R^2			44%

DnB NOR ARI Prisma

	α	β	P
C	0,003		0,56
r_m-r_f		0,355	0,00
SMB		0,280	0,43
HML		0,450	0,05
TERM		1,771	0,00
JPGBI		-3,127	0,00
MT		-0,503	0,32
GDP*r_m		0,000	0,41
TCW*r_m		-0,023	0,87
GDP*SMB		0,000	0,79
TCW*SMB		-0,154	0,13
GDP*HML		0,000	0,11
TCW*HML		0,216	0,02
GDP*TERM		0,000	0,54
TCW*TERM		-0,232	0,02
GDP*JPGBI		0,000	0,19
TCW*JPGBI		0,447	0,02
GDP*MT		0,000	0,54
TCW*MT		0,006	0,97
R^2			76%
Adj. R^2			51%

Erik Penser Hedgefond

	α	β	P
C	0,004		0,61
r_m-r_f		0,355	0,00
SMB		0,519	0,12
HML		0,707	0,10
TERM		1,048	0,01
JPGBI		-1,877	0,01
MT		-0,460	0,35
GDP*r_m		0,000	0,99
TCW*r_m		0,056	0,63
GDP*SMB		0,000	0,28
TCW*SMB		-0,110	0,30
GDP*HML		0,000	0,27
TCW*HML		0,193	0,06
GDP*TERM		0,000	0,79
TCW*TERM		-0,190	0,06
GDP*JPGBI		0,000	0,60
TCW*JPGBI		0,484	0,02
GDP*MT		0,000	0,95
TCW*MT		-0,090	0,51
R^2			65%
Adj. R^2			28%

Guide Hedgefond

	α	β	P
C	-0,006		0,37
r_m-r_f		0,241	0,05
SMB		0,125	0,73
HML		0,580	0,06
TERM		1,182	0,00
JPGBI		-1,720	0,02
MT		0,124	0,83
GDP*r_m		0,000	0,14
TCW*r_m		-0,103	0,44
GDP*SMB		0,000	0,41
TCW*SMB		-0,143	0,17
GDP*HML		0,000	0,16
TCW*HML		0,209	0,07
GDP*TERM		0,000	0,95
TCW*TERM		-0,203	0,06
GDP*JPGBI		0,000	0,67
TCW*JPGBI		0,383	0,09
GDP*MT		0,000	0,23
TCW*MT		0,085	0,52
R^2			65%
Adj. R^2			27%

H&Q Global Hedge

	α	β	P
C	-0,003		0,74
r_m-r_f		0,323	0,00
SMB		0,427	0,21
HML		0,735	0,00
TERM		1,597	0,00
JPGBI		-2,969	0,00
MT		-0,360	0,52
GDP*r_m		0,000	0,44
TCW*r_m		-0,095	0,53
GDP*SMB		0,000	0,37
TCW*SMB		-0,153	0,13
GDP*HML		0,000	0,16
TCW*HML		0,260	0,02
GDP*TERM		0,000	0,38
TCW*TERM		-0,309	0,00
GDP*JPGBI		0,000	0,16
TCW*JPGBI		0,692	0,01
GDP*MT		0,000	0,48
TCW*MT		0,086	0,62
R^2			75%
Adj. R^2			49%

H&Q Nordic Hedge

	α	β	P
C	0,002		0,76
r_m-r_f		0,277	0,04
SMB		0,409	0,20
HML		0,526	0,04
TERM		1,486	0,00
JPGBI		-2,585	0,00
MT		-0,472	0,40
GDP*r_m		0,000	0,43
TCW*r_m		-0,061	0,70
GDP*SMB		0,000	0,68
TCW*SMB		-0,064	0,49
GDP*HML		0,000	0,25
TCW*HML		0,205	0,04
GDP*TERM		0,000	0,94
TCW*TERM		-0,272	0,02
GDP*JPGBI		0,000	0,55
TCW*JPGBI		0,395	0,04
GDP*MT		0,000	0,44
TCW*MT		0,033	0,81
R^2			71%
Adj. R^2			40%

H&Q Solid

	α	β	P
C	0,001		0,95
r_m-r_f		0,356	0,00
SMB		0,359	0,33
HML		0,647	0,01
TERM		1,567	0,00
JPGBI		-2,888	0,00
MT		-0,348	0,58
GDP*r_m		0,000	0,51
TCW*r_m		-0,093	0,53
GDP*SMB		0,000	0,57
TCW*SMB		-0,170	0,09
GDP*HML		0,000	0,22
TCW*HML		0,240	0,02
GDP*TERM		0,000	0,56
TCW*TERM		-0,269	0,01
GDP*JPGBI		0,000	0,33
TCW*JPGBI		0,545	0,04
GDP*MT		0,000	0,63
TCW*MT		0,081	0,63
R^2			74%
Adj. R^2			47%

Handelsbanken`s Hedgefond Aktie

	α	β	P
C	-0,003		0,67
r_m-r_f		0,320	0,00
SMB		0,157	0,63
HML		0,543	0,02
TERM		1,396	0,00
JPGBI		-2,656	0,00
MT		-0,212	0,65
GDP*r_m		0,000	0,11
TCW*r_m		-0,072	0,53
GDP*SMB		0,000	0,87
TCW*SMB		-0,081	0,22
GDP*HML		0,000	0,22
TCW*HML		0,259	0,00
GDP*TERM		0,000	0,43
TCW*TERM		-0,216	0,03
GDP*JPGBI		0,000	0,26
TCW*JPGBI		0,476	0,02
GDP*MT		0,000	0,33
TCW*MT		0,010	0,93
R^2			78%
Adj. R^2			55%

Libra

	α	β	P
C	-0,005		0,34
r_m-r_f		0,176	0,14
SMB		0,144	0,56
HML		0,528	0,10
TERM		1,590	0,00
JPGBI		-2,981	0,00
MT		0,166	0,73
GDP*r_m		0,000	0,05
TCW*r_m		-0,125	0,48
GDP*SMB		0,000	0,68
TCW*SMB		-0,151	0,11
GDP*HML		0,000	0,33
TCW*HML		0,280	0,03
GDP*TERM		0,000	0,04
TCW*TERM		-0,222	0,10
GDP*JPGBI		0,000	0,04
TCW*JPGBI		0,477	0,12
GDP*MT		0,000	0,42
TCW*MT		0,151	0,34
R^2			71%
Adj. R^2			40%

Nordea European Equity Hedge Fund

	α	β	P
C	-0,004		0,59
r_m-r_f		0,287	0,00
SMB		0,246	0,42
HML		0,642	0,03
TERM		1,275	0,00
JPGBI		-2,086	0,00
MT		-0,104	0,84
GDP*r_m		0,000	0,26
TCW*r_m		-0,058	0,65
GDP*SMB		0,000	0,20
TCW*SMB		-0,083	0,24
GDP*HML		0,000	0,20
TCW*HML		0,249	0,01
GDP*TERM		0,000	0,43
TCW*TERM		-0,255	0,02
GDP*JPGBI		0,000	0,23
TCW*JPGBI		0,613	0,02
GDP*MT		0,000	0,49
TCW*MT		0,043	0,69
R^2			71%
Adj. R^2			40%

SEB Multihedge

	α	β	P
C	0,007		0,33
r_m-r_f		0,306	0,01
SMB		0,679	0,14
HML		0,374	0,31
TERM		1,054	0,06
JPGBI		-2,032	0,03
MT		-1,294	0,06
GDP*r_m		0,000	0,27
TCW*r_m		-0,122	0,48
GDP*SMB		0,000	0,63
TCW*SMB		-0,072	0,59
GDP*HML		0,000	0,06
TCW*HML		0,243	0,05
GDP*TERM		0,000	0,76
TCW*TERM		-0,504	0,01
GDP*JPGBI		0,000	0,97
TCW*JPGBI		0,826	0,04
GDP*MT		0,000	0,76
TCW*MT		-0,060	0,68
R^2			70%
Adj. R^2			38%