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Performance of Hedge Funds in the European Market

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ABSTRACT

The aim of this paper is to investigate the performance of hedge funds during the period between December 1999 and March 2012. We consider 8 different investment styles for the European market. As it has been argued in several papers hedge funds differ from traditional funds, since it allows for diversification and lower systematic risk. Previous studies show inconclusive results regarding whether hedge funds are able to beat the market. In order to find evidence for the existence of abnormal returns for the hedge funds we regress 3 different asset pricing models, static CAPM, Fama-French three factor model and dynamic Multi-factor model. In line with our expectations the Multi-factor model is better suited to capture the dynamic risk exposures of the hedge funds since it includes additional risk factors as well as instrumental variables, taking into account the effects of the business cycles. We investigate the performance of the hedge funds in 3 different sub-periods and find that for some of the investments strategies it is possible to obtain positive anomalies in returns. However, the empirical results demonstrate that the number of significant alpha's from the various models change over time and strategies.

Keywords: Hedge funds, asset pricing models, Multi-factor model, investment strategies, performance measures.

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1. INTRODUCTION

In the introductory chapter we aim to provide the reader with the background of the topic, problem discussion and specification on the current state of research which will constitute the foundation of the purpose. In addition, limitations and comprehensive outline of the study will be presented.

1.1 Background

During the past two decades, we have seen 25 percent of growth in alternative investments vehicles like hedge funds. With approximately 10 000 active hedge funds worldwide estimated to be a $2 trillion industry (Hedge Fund Association), increasing their prominence in the financial market and providing investors with opportunities to manage risks and achieve absolute returns. Perhaps, mainly because of the beneficial features of hedge funds, unlike mutual funds, containing low systematic risk due to its low correlation with traditional asset classes as well as limited government oversight (Ackermann, C., McEnally, R., & Ravenscraft, D., (1999), Liang, B. (1999), Agarwal, V., & Naik, N.Y. (2000)).

Despite the fact of recent focus on hedge funds, the alternative investment vehicle has been in existence since the year of 1949 and can be attributed to Alfred W. Jones. As he created an investment fund as a general investment partnership, he had the idea of a (non directional / market neutral) hedge fund that involved taking a long position in undervalued assets and at the same time taking short position in overvalued assets. This innovation enabled investors to make large bets with limited resources by an effectively leveraged investment capital. (Brown, S.J., Goetzmann, W.N., & Ibbotson, R.G., 1999)

In general, there have been evidence showing both positive (absolute) return and performance persistence (Edwards, F.R., & Caglayan, M.O., 2001). Investing in mutual funds will on average underperform passive investment strategies that typically don't actively attempt to profit from short term fluctuations. The basic idea of hedge funds is to reduce volatility and risk, at the same time yield high absolute returns in both bull- and bear markets. Thus, by employing different unconventional investment strategies will allow the hedge fund manager to instantly adapt and benefit from the volatile market. (Agarwal, & Naik, (2000), Fung, W., & Hsieh, D.A., (2000), Edwards, F.R., & Caglayan, M.O., (2001)

1.2 Problem Discussion

With the intention of analyzing hedge fund performances the majority of previous studies often use static/unconditional asset pricing models, such as CAPM and Fama-French three factor model, ignoring the time variation and overall ignoring the changing state of economy. The problem of these model have as a consequence shifted focus towards conditional models, allowing for time variability in order to overcome problems associated with different conditional models. However, as previous studies in the field have given numerous inconclusive findings regarding hedge fund performance applying static models, we will therefore consider a further throughout research in the field applying both unconditional and conditional models. This is necessary from both academics as well as an investor's point of view, in order to both overcome these problems and finding whether hedge funds really do add value in terms of return.

1.3 Purpose

The purpose of this paper is to investigate and contribute to our understanding of the performance of European hedge funds given different hedge fund styles. With the intention of finding whether it is possible to produce excess returns, we apply different performance methods, both conditional and unconditional models.

1.4 Limitations

We conduct this investigation using data provided from Eurekahedge, based on a set of currently active European hedge funds which covers the available data sample of returns between December 1999 and March 2012, including two distress periods (IT-bubble and real estate-bubble). We will consider the European region as one unit, as the European index comprises funds that are allocated to Europe, rather than individual countries.

1.5 Outline

The following chapter will provide a presentation of relevant theoretical issues and empirical findings. In chapter three, data selection and work procedure will be clarified and specified as well as relevant asset pricing models in addition potential biases will be discussed. In the fourth chapter we present and analyze empirical findings. The final chapter will contain the most important conclusions and suggestions for further research in the field.

2. THEORETICAL FRAMEWORK

This chapter will explain the relevant theories. Firstly we will present historical background and definition of hedge funds then followed by comparison to traditional investment vehicles. Additionally, the reader will be given explanation of relevant past findings as well as asset pricing models, performance measures and its risk factors and instruments. We conclude the chapter by reviewing different statistical properties. The theoretical framework will stand as a good base for further analysis of the empirical findings.

2.1 Hedge Fund History

The conception of a hedge fund goes back to the year of 1949, when Alfred W. Jones, an Australian journalist, came to the idea of short selling the overvalued stocks and simultaneously going long in undervalued ones. He found out that this investment style known also as a market neutral strategy, would result in gaining profits no matter in which direction the market moves. Thus, the returns would depend on investors' skills in choosing right stocks but not the overall market reactions. He used leverage to purchase more shares and enhance the returns and at the same time stayed away from risk exposures by short selling. This combination made his investment strategy conservative and reduced the effects of the market movements. This market neutral strategy has been followed by most hedge funds during 1970's. Although the start was quit slowly, the numbers of the hedge funds rose up quickly during 1990's which also resulted in various investment strategies. (Brown, Goetzmann, & Ibbotson, 1999)

2.2 Hedge Funds versus Traditional Investment Funds

According to empirical studies, there are several differences between hedge funds and mutual funds. In contrast with traditional investment vehicles, due to their numerous investment styles the systematic risk is lower for the hedge funds as they allow for diversification. Hedge funds' limited regulations facilitate the investment decision making for their managers, meanwhile the special fee structure gives incentive to the managers to perform more in line with investors' interests compared to the mutual funds. In contrast with traditional funds, the fee depends on the performance rather than size of the asset. Additionally, due to its higher water mark, the fee is only achievable when the managers make up the previous losses which can be counted as another motivation. Diverse return targets can also be considered as another difference between these two types of funds. Hedge funds are absolute performers while on the other hand mutual funds are relative performers as their performance judge against benchmarks like S&P 500 index. All in all, most of the times hedge funds show better performance than mutual funds. (Liang, 1999)

Another difference is the restricted availability of the hedge funds. Mutual funds are easily in the access of all groups of people with different wealth level, whilst hedge funds are only on hand for special group of investors with higher wealth. It is possible to make money out of hedge funds even at the time of down market, since its performance is regardless of the market's movement. Fund managers' personal investment in the hedge funds is more common compared to the traditional funds. Besides, their measurement for performance differs, since the successful mutual fund has to outperform the market index whereas the success of the hedge fund relies on the higher return due to its risk exposures. (Anderlind, P., Eidolf, E., Holm, M., Sommerlau, P., 2003)

2.3 Hedge Fund Definition

The meaning of hedge funds commonly refers to a general limited investment partnership. The word *hedge* stems from protecting your investments with the objective of mitigating risk exposure and making absolute returns on their underlying investments from market uncertainty, i.e. generating positive returns in both up and down markets (Brown, Goetzmann, & Ibbotson, 1999). Hedge funds are of interest to both academics as well as investors due to their return profiles that significantly differs from mutual funds (Fung & Hsieh, 2000). However, with a minimum investment ranging from $250,000 to $10,000,000 or more, hedge funds can undertake any financial instrument and non-traditional trading strategies (directional- and non-directional) unlike other funds, hence allowing for diversification opportunities. For this reason we have seen a steady growth of 25 percent in alternative investment vehicles like hedge funds, meaning that both the number and capital controlled have increased their prominence in the financial market. However, as a result of the rather limited regulation, it is with difficulty to say how many active hedge funds really exist, as there are no regulations of having publicly available information regarding the operations of alternative investments like hedge funds. Currently, there approximately exist 10 000 reported active hedge funds worldwide and the number is growing every day, estimated to be a $2 trillion industry (Hedge Fund Association). According to Anderlind et al. (2003) 80 percent of the active hedge funds are located in US, 13 percent in UK, 4 percent in Asia and remaining 3 percent in Europe. Even if the European hedge fund market is still fairly small as well as new, it is still regarded as the market with the highest current growth rate compared to others. (Anderlind et al., 2003)

2.4 Investment Strategies

We will closer investigate 8 hedge fund strategies. In line with Agarwal and Naik (2000) we separate the different strategies according to whether they are directional, non-directional or miscellaneous.

2.4.1 Directional Strategies

Strategies with high correlation with the market utilize the market movements and are referred as directional:

Long Short Equities: This investment style focuses on short selling the equities that are overvalued and expected to decrease in value and buying long undervalued securities that are likely to have increase in value. By this investment strategy the market risk can be neutralized and it can produce optimal risk-adjusted returns. This style is a combination of three strategies long equities, short equities and modest leverage.

Macro: This is a very elastic strategy since it is used in various markets that are expected to give the best opportunities. This investment style is a combination of leverage and long positions which has an effect on securities, currency rates, commodities, fixed incomes and interest rates. Appropriate timing is the key element for success in this investment style.

CTA/Managed Futures: This strategy is known as Commodity Trading Advisors. This strategy combines long and short positions in order to yield returns in both up- and down markets. The funds generally invest in currency markets plus options and futures.

2.4.2 Non-Directional Strategies

In the case of low correlation with the market, the classic market neutral strategy is classified as non-directional:

Event Driven: Investment strategy that focuses on investing in situations where there is some form of corporate activity or change i.e. exploring inconsistencies in the markets before/after corporate events takes place, by taking a position in undervalued security that is expected to rise in value due to the event. These corporate activities can refer to merger and acquisitions (M&A), recapitalizations or liquidations to mention few (Agarwal & Naik, 2000). The main risk is tied to the probability of event not occurring.

Fixed Income: By employing fixed income strategy, the hedge fund manager is able to earn relative value and maximize its arbitrage opportunities by exploiting price anomalies between fixed income securities and derivatives. According to Agarwal and Naik (2000) the risk of the fund varies and depend on duration, credit exposure and leverage employed.

Arbitrage: An investment approach that involves buying a security or other financial instrument in one market and simultaneously shorting a similar instrument in another market. Hence, hedge managers can profit from price anomalies as a result of market inefficiencies.

Relative Value: It is an investment strategy that consists of managers simultaneously taking long and short positions in related financial instruments that are expected to appreciate and depreciate respectively, by doing so it allows investors to profit from the relative value of the instruments.

In addition to the main categories a third category will be presented, Multi-Strategy as it can be applied across the sub-groups:

Multi-strategy: This strategy is a combination of several investment styles such as convertible bond arbitrage, long short equity, statistical arbitrage and merger arbitrage. This diversification allows for lower volatility as well as smoother returns. These positive returns are not dependent on direction of the market movements.

2.5 Previous Studies

During the last decades there have been a lot of researches done concerning hedge funds as a result of their fast growth and the performance of the hedge fund is controversial according to different studies. Some investigators believe that hedge fund returns are worse than what have been expected because of their several biases as well as their high fees (Malkiel & Saha 2005), while in contrast many of other studies show greater performance of hedge funds compared with mutual funds.

Liang (1999) investigated the performance of hedge funds for a period of 5 years, starting from January 1992 until December 1996. In line with Fung and Hsieh (1997), Liang (1999) argue that an investor holding a hedge fund portfolio will gain more than the one holding a traditional mutual fund portfolio, since the hedge fund allows for diversification among

different strategies which don't have high correlation with each other. On the other hand, the compensation of mutual fund is related to the fund size while the fee of the hedge fund depends on its performance. According to his findings, hedge funds present higher Sharpe ratios as well as lower betas which consequently results in a greater performance compared with the traditional mutual funds.

Ackermann, McEnally and Ravenskraft (1999) studied the performance of the hedge funds considering return, risk and managerial incentives from 1988 to 1995. They compared hedge funds with both mutual funds and standard market indices and conclude that while hedge funds do better than the former they still don't outperform the latter. They explained the superior performance of the hedge funds by referring to several characteristic such as their elastic investment styles and enticement fees as well as less governmental regulation.

Brown, Goetzmann and Ibbotson (1999) analyzed the performance of the offshore hedge funds in US as a representative of the industry since the offshore funds consist of the most important hedge funds. By applying unconditional CAPM, they found the evidence for lower average annual return as well as lower standard deviation of the offshore hedge funds compared to S&P 500 index, for the same period as Ackermann, McEnally and Ravenskraft (1999). Their empirical study resulted in finding positive risk-adjusted returns for offshore funds measured by Jensen's alpha and Sharpe ratios.

Edwards and Caglayan (2001) used monthly returns of eight different investment strategies between January 1990 and August 1998. Their results signified the fact that the hedge funds abnormal returns depend on the type of the investment styles. However, using conditional multifactor models, only twenty five percent of the hedge funds of their sample provided positive risk-adjusted excess returns measured by the significant estimated alphas. They also found considerable performance persistence over one- and two year scopes. As they mentioned in their article, managerial skills in addition to incentive payments of the hedge funds could count as some reasonable explanations for their remarkable performance.

In line with Edwards and Caglayan (2001), Kat and Miffre (2003) applied multifactor models in order to investigate the performance of the hedge funds during the period of 1990 to 2000. However, in contrast with the results of Edwards and Caglayan (2001), more than three quarter of the hedge funds in the sample yielded abnormal returns.

2.6 Asset Pricing Models

The factor models break down the return of the asset into different factors. These models identify the risk factors and can be used to compute the sensitivities of the assets to these factors. In general, factor models for asset returns are mostly used in order to decompose the risk and return into reasonable components and estimate the anomalous returns of the assets. They also measure the volatility of the returns as well as the covariance among them. These models allow for predicting future returns in different situations.

2.6.1 CAPM

The one-factor Capital Asset Pricing Model, introduced by Sharpe, W. (1964) and Lintner, L. (1965), implies that the security's return can be explained adequately by the assets' sensitivity to the market portfolio (beta). This model also takes into account the market expected return as well as the expected return of the risk free asset. Beta is the non-diversifiable risk which calculates the riskiness of the asset compared to the market. The security will have more volatility that the market if the beta is superior than one and vice versa. The higher the risk is the higher the expected return will be.

CAPM is based on several basic assumptions. In this model the utility-maximizing investors are risk averse and they only care about the variance and mean respectively as a measure of risk and return. The information is the same among all the investors, implying homogenous expectations. In other words, by using the same inputs, investors expect the same amount of risk and return. Besides, asset prices take into account all the accessible public information and rapidly adjust to the new information released in the market. The market is also assumed to be complete i.e. there are no taxes and transaction costs, the prices are not affected by investors and at the risk free rate limitless borrowing and lending is permitted. The portfolio lies on the efficient frontier so it can be optimized by having the lowest possible level of risk for its level of return. In order to analyze the performance of the hedge funds we consider the excess returns yielded by the eight different strategies in Europe. Sharpe and Lintner (1964) hence argue that if investors hold homogenous expectations, mean-variance efficient portfolio and the markets are assumed to be complete, the portfolio will itself will be considered to be a mean-variance efficient portfolio. We apply CAPM by running the OLS time series regression:

$$R_{it} - R_{ft} = \alpha + \beta(R_{mt} - R_{ft}) + \varepsilon_t$$

Whereas R_{it} is the expected monthly return of each hedge fund's investment style at time t, R_{ft} is the risk free rate (one month Treasury bill rate), R_{mt} is the return on the market portfolio, ε_t represents the error term. α and β are regression parameters. We run the regression in terms of excess returns ($R_{it} - R_{ft}$) on the market risk premium, ($R_{mt} - R_{ft}$). The beta coefficient stands for the measure of risk. (Campbell, J.Y., Lo, A.W., & Mackinlay, A.C., 1997)

2.6.2 Fama-French Three Factor Model

In order to describe the stock returns, in contrast with one variable CAPM, Fama, E. and French K.R. (1992) introduced the three factor model which was superior in explicating asset returns over time. They discuss the fact that average returns are also related to other risk factors such as size and book-to-market value, since the traditional asset pricing model's risk factor solely wouldn't be able to capture these return anomalies. So as to investigate the performance of hedge funds we use Fama-French three factor model:

$$R_i - R_f = \alpha_i + \beta_i(R_m - R_f) + \gamma_i \, SMB + \delta_i \, HML + \varepsilon_i$$

β, $\boldsymbol{\gamma}$ and $\boldsymbol{\delta}$ are counted as the factor sensitivities of returns. ($R_m - R_f$) is the market risk premium. SMB, is the measure for the size premium and HML accounts for value- over growth stocks (Fama & French, (1996), Ogden, J.P., Jen, F.C. & O'Connor, P.F, (2002)).

2.6.3 Conditional Factor Model

Ferson and Schadt (1996) state that in the case of having time varying mean and variance, the unconditional CAPM and Fama-French three factor model are not reliable since they can't capture the dynamics. They investigated the performance of fund strategies in changing economic conditions.

Conditional factor approach was proposed by Ferson and Harvey (1999) in order to allow for time-varying parameters as linear functions of instruments. Such instruments or conditioning variables could represent the different economic conditions such as business cycles. Ferson and Harvey (1999) introduced the general framework for conditional factor models:

$$E_t(r_{i,t+1}) = \alpha_{it} + \beta'_{it} \, E_t(r_{p,t+1})$$

$$\beta_{it} = b_{0i} + b'_{1i} Z_t$$

$$\alpha_{it} = \alpha_{0i} + \alpha'_{1i} Z_t$$

Where $r_{i,t+1}$ is the stock return at time t+1, $r_{p,t+1}$ is a vector of excess returns on the risk factor-mimicking portfolios at time t+1, Z_t is a vector on conditioning variables at time t, α_{it} shows the abnormal returns, b_{0i} is the mean of conditional beta and β_{it} is the coefficient of conditional beta regarding Z_t. Since b'_{1i} is a fixed coefficient, the equation above demonstrates a fixed linear relationship among betas and conditioning variables for any given portfolio. We can reach the multi factor model by combining the formulas mentioned above:

$$r_{i,t+1} = (\alpha_{0i}+\alpha'_{1i} Z_t)+(b_{0i}+b'_{1i}Z_t)r_{p,t+1}+\varepsilon_{i,t+1}$$

In order to be able to capture the risk exposures of the hedge fund returns, in line with Ferson and Schadt (1996), Gupta, Cerrahoglu and Daglioglu (2003) used conditional variables approach rather than traditional models. Considering hedge funds' dynamic investment strategies and their high volatility over time, they argued that time varying regressions are more appropriate for measuring the performance of the hedge funds. All things considered, it seems that applying conditional factor models would be a better choice which facilitates capturing the performance of the different hedge fund strategies.

As suggested by previous empirical studies, additional risk factors as well as instrumental variables should be included to explain the variance of the model and to characterize the behavior of expected returns. Connor, G. and Korajczyk, R. (1988) and Lehmann, B. and Modest, D. (1988) argue that five risk factors are adequate amount of factors. Since their study showed that including more than five risk factors didn't affect the results significantly. The regression model applied will be presented below:

$$R_i-R_f= \alpha_{i0} +\beta_{i1}(R_m-R_f) + \beta_{i2}SMB+ \beta_{i3}HML + \beta_{i4}MOM + \beta_{i5}MT + \beta_{i6}(VIX(R_m-R_f) + \beta_{i7}(IPI(R_m-R_f) + \beta_{i8}(VIX\cdot SMB) + \beta_{i9}(IPI\cdot SMB) + \beta_{i10}(VIX\cdot HML) + \beta_{i11}(IPI\cdot HML) + \beta_{i12}(VIX\cdot MOM) + \beta_{i13}(IPI\cdot MOM) + \beta_{i14}(VIX\cdot MT) + \beta_{i15}(IPI\cdot MT) + \varepsilon_i$$

2.6.4 Risk Factors

The motivation of using five risk factors in the conditional multi-factor model is as follows:

R_m-R_f The reason behind including the market factor as a source of risk is motivated entirely by CAPM (Fama & French, 1993).

SMB: Liew, J. and Vassalou, M. (2000) argue that SMB captures innovations in economic growth expectations and inflation. According to Fama and French (1993) small caps are riskier than large caps and therefore will yield higher absolute returns and are hence a proxy for the size risk.

HML: According to Fama and French (1993) the book-to-market ratio is related to higher return and in line with Liew and Vassalou (2000) HML would capture information that is relevant in predicting the economic growth.

MOM: The explanation of including MOM as a risk factor is utterly based on results and recommendations from Carhart's (1997), Liew and Vassalou's (2000) and Jegadeesh, N. and Titman, S. (1993).

MT: Previous studies have showed inconclusive findings regarding the managers market timing ability (Chen, L., & Liang, B., (2007), Fung, H.G, Xu, W.E., & Yau, J., (2002)).

2.6.5 Instruments

The instrumental variables included, is used as proxies for the overall market condition and business cycles, as a way of capturing the time variability.

VIX: Similar to Whaley, R.E. (2000) we ought to include the volatility index.

IPI: As the European gross domestic product is reported quarterly, construction of monthly values would create certain biases, we therefore choose to include industrial productivity as a proxy for business cycles in Europe.

2.7 Performance Measures

With the purpose of estimating the performance of the hedge funds in Europe from December 1999 to March 2012, we use two distinguished performance measures, Jensen's alpha and the Sharpe ratio.

2.7.1 Jensen's Alpha

Jensen's alpha is the intercept of asset pricing models which shows the performance of the returns. CAPM returns are risk-adjusted as they allow for all the riskiness of the assets. The positive Jensen's index is a sign for the existence of positive abnormal returns in other words it indicates higher asset returns compared to risk-adjusted returns. If the alpha is equal to zero we will have the standard CAPM.

$$R_{it} - R_{rt} = \alpha + \beta(R_{mt} - R_{ft})$$
$$\alpha = R_{it} - [R_{rt} + \beta(R_{mt} - R_{ft})]$$

2.7.2 Sharpe Ratio

The Sharpe index is a measure of risk premium per each unit of risk which shows the balance between the taken risk and expected return on the asset. Comparing two assets, the one with higher Sharpe ratio indicates higher return for the same level of risk.

$$S = \frac{E(R_i) - R_f}{\sigma}$$

This index is calculable from any series of returns even with the lack of extra information about the sources of profitability. However, despite this advantage, for reliable results the data should be normally distributed so anomalies such as skewness or kurtosis may cause some problems for this ratio.

2.8 Statistical Properties

To enable reliable empirical conclusions we need to consider some statistical properties. In regression analysis, when applying time series data one needs to find whether the data can be considered as being valid. Generally, when applying OLS with the purpose of estimating parameters it is essential to find the data to be BLUE (Best Linear Unbiased Estimator), showing the lowest possible mean squared error (MSE). If tests signify autocorrelation and/or heteroskedasticity within the regression, as a consequence the results will no longer be considered BLUE. Hence adjustments of data will be needed in order to obtain efficient and reliable estimators, otherwise confidence intervals and hypothesis tests will be ambiguous. Further on, we will examine various statistical properties.

2.8.1 Stationarity

According to Brooks (2008) we ought to test the data for non-stationarity, in order to find out whether we can reject the null of unit root, against the alternative hypothesis of stationarity. We perform an Augumented Dickey-Fuller (ADF) test type and use the test-statistic, following DF-critical values in additional to the probability, in order to find whether we can reject the null or not.

$$\text{ADF: } \Delta y_t = \psi\, y_{t-1} + \sum_{i=1}^{P} \alpha_i \Delta\, y_{t-1} + u_t \qquad \text{where the t-Statistics} = \frac{\hat{\psi}}{\widehat{SE}(\hat{\psi})}$$

2.8.2 Autocorrelation

Autocorrelation is related to the problem of residuals being serially dependent of each other. As the presence of positive serial correlation violates the OLS assumption, we will have to account for problems related to statistical tests not being valid and reliable due to misleading standard errors. To facilitate the problem, we initially need to examine the presence of autocorrelation which can be done by applying traditional tests like Durbin-Watson statistics.

2.8.2.1 Durbin-Watson statistics

In line with Durbin J. and Watson G.S. (1951) we test the null that the errors are serially independent against the presence of first order autocorrelation. The test statistics is

$$d = \frac{\sum(e_t - e_{t-1})}{\sum e_t^2} \qquad 0 < d \leq 4$$

e_t is the residual at time t. If d>1, this implies positive serial correlation, whilst d<3 shows evidence of negative autocorrelation. The rule of thumb signifies that d=1 indicates no autocorrelation.

2.8.3 Heteroskedasticity

When the variance of the errors are not constant and finite, $\text{var}(e_t) \neq \sigma^2$ this will be of concern in the application of regression analysis, as the presence will make the statistical tests invalid (Brooks, C., 2008). The case with heteroskedasticity will as a fact not imply biased OLS estimators, but will involve biased residuals. Consequently, the data will provide deceiving standard errors and our inferences might as a result not be correct. We use the statistical test called the White test in order to establish whether the residual variance is constant, $\text{var}(e_t)=\sigma^2$. Thus, we test the null of no heteroskedasticity against the presence of heteroskedasticity

(White, H., 1980). If the auxiliary regression analysis demonstrates that the dataset contains heteroskedastic residuals one needs to apply the heteroskedastic-consistent covariance matrix estimator in order to ensure unbiased residuals by adjusting the p-values.

2.8.4 Multicollinearity

When there is a relationship between two or more independent variables in a multiple regression one might say that the regression suffers from multicollinearity. An important statistical issue that is tied to the problem with collinearity and needs to be considered, is related to spurious regressions. In order to identify this problem we will apply a correlation matrix between all the explanatory variables, according to Brooks (2008) a correlation coefficient in the range of 80% has to be considered. As a possible remedy Brooks (2008) suggests one to exclude the variable that hold the highest level of correlation.

2.8.5 Skewness

The skewness is referred to the third standardized moment of a random variable and defined as:

$$\gamma_1 = \mathrm{E}\left[\left(\frac{x-\mu}{\sigma}\right)^3\right] = \frac{\mu_3}{\sigma^3}$$

In order to detect the distribution of the hedge fund returns, one needs to take into consideration the skewness. It is a measure of the asymmetry of the probability distribution of stochastic variable. For left-skewed or left-tailed distribution, the skewness is negative and vice versa. (Gujarati, D., 2006)

2.8.6 Kurtosis

Similar to skewness, kurtosis is another measure which describes the shape of the probability distribution. However, unlike with skewness, this measure is based on the fourth moment of the return data. Kurtosis can clarify the fatness of the distribution's tails. The fourth standardized moment minus 3 is defined as excess kurtosis which is used as an adjusted version of kurtosis.

$$\gamma_2 = \frac{\mu_4}{\sigma^4} - 3$$

The formula indicates that for a normal distribution, the excess kurtosis should be zero so the kurtosis would be three. Positive excess kurtosis means that the distribution has fatter tails and higher peaks around the mean. This is also known as leptokurtic distribution while on the other hand a platykurtic distribution with negative excess kurtosis contains thinner and lower peaks around the mean. (Gujarati, 2006)

2.8.7 Normality

In order to check whether the returns have normal distribution, the Jarque-Bera test is applicable. This test checks if the skewness and kurtosis of the data is close to a normal distribution. The null hypothesis tests out whether skewness and excess kurtosis are jointly equal to zero in other words if the sample returns are normally distributed. For the normally distributed data, JB has a chi-squared distribution with two degrees of freedom.

$$JB = \frac{n}{6}\left(\gamma_1^2 + \frac{1}{4}\gamma_2^2\right)$$

3. METHODOLOGY

The following chapter will clarify and motivate the data selection process and the general method of work in addition to specifying the chosen risk factors, pre-determined conditioning variables and conclude the chapter with potential biases.

3.1 Motivation

As the objective for this research is to evaluate the performance of different hedge fund strategies throughout different market conditions, we are therefore aiming to investigate whether hedge fund managers are capable of producing excess returns. Furthermore, we use quantitative data and empirically testing eminent performance models following a deductive approach, i.e. by starting with hypothesis and then collect empirical data in order to find whether we can reject or not reject our hypothesis and thereon draw conclusions. In line with Jacobsen D.I. (2002) and Halvorsen K. (1992) we believe that the deductive approach is the best suited and seem logical for the purpose of the investigation as well as to capture the concepts of reality.

3.2 General Method of Work

To begin with, we collect our data sample from diverse databases during the period between December 1999 and March 2012 consisting of 148 monthly observations for 8 different hedge fund investment styles, with the motivation of being able to capture the excess returns in both down- and up markets as we include both IT bubble as well as real-estate bubble. We transformed the price index into returns with the following formula:

$$R_i = ln\left(\frac{p_t}{p_{t-1}}\right) \cdot 100\%$$

We obtained the monthly excess returns by taking the difference between Ri and the one month T-bill, R_f. The excess returns are then estimated using Ordinary Least Squared (OLS) against various independent variables. The estimations are performed on CAPM, Fama-French Three factor model and a Conditional Multi-factor model which allows for time-variability. Additionally, we test whether the data suffers from autocorrelation and heteroskedasticity. In order to improve the OLS regression, we apply the Newey-West estimator to adjust for autocorrelation and heteroskedasticity (HAC).

3.3 Data

The theoretical population corresponds to all the European countries, as indices are more precise we believe that using the equally weighted index tracking the Europe industry would be sufficient to capture the reality. The data sample is brought from different sources including the Eurekahedge database where we found 148 monthly returns (net of all fees) observations for 8 hedge fund styles since December 1999, to ensure a sufficient number of consecutive observations to test some of the theories discussed. Other sources include Thomson Reuters DataStream and Kenneth R. French data library.

Since neither daily nor weekly return data were available, the motivation of using monthly- instead of annual returns, apart from giving more observations, enables us to track the hedge fund return fluctuations more closely as well as enhances the accuracy of the standard deviations. (Ackermann, McEnally, & Ravenscraft (1999), Brown, Goetzmann, & Ibbotson (1999))

Further, we will present the sources of our risk factors and pre-determined conditioning variables:

R_i: The return on 8 European hedge fund investment styles, including Arbitrage, CTA/Managed Futures, Event Driven, Fixed Income, Long Short Equities, Macro, Multi-Strategy, Relative Value and the data sample is obtained from Eurekahedge.

R_M: Is the market return on the whole stock market and used as a proxy for the market (Fama & French, 2003). The data is obtained from Kenneth R. French data library.

R_f: Stands for the risk free return rate (one month T-bill), collected from the Kenneth R. French data library.

R_m-R_f Is consequently the excess return on the market.

SMB: Represents the spread in the returns between low-book-to-market stocks and high-book-to-market stocks and constructed by forming value weighted

portfolios on size and BM (book-to-market) and measures the past excess returns of small- over big caps. Data is obtained from the Kenneth R. French data library.

HML: The data is obtained from Kenneth R. French data library and represents the spread in the returns between high B/M and low B/M stocks. HML accounts for the past excess returns of value- over growth stocks.

MOM: Momentum represents the difference between the average return on the portfolio of past winners and portfolio of past loser.

MT: Is the market timing factor, $\max[(R_m-R_f)^2, 0]$, the risk factor investigates if the fund manager can account for the market timing ability, managers exhibiting market timing ability will be able to earn higher abnormal returns when markets are expected to rise and vice versa (Gupta et. al., 2003).

The pre-determined conditioning variables are:

VIX: The volatility index VSTOXX stands as a measure of the market's perception of risk and are designed to reflect market expectations of volatility in the European equity market. The VIX-data is obtained from DataStream.

IPI: Industrial productivity measures the real production output and is used as a proxy for business cycles in Europe. The data for industrial productivity is monthly and given by DataStream. As the data for IPI exhibit seasonal variation, for each month we use the average of the previous 12-months to adjust and remove this cyclic variation.

3.4 Potential Biases

Whilst interpreting empirical results one needs to have potential biases in mind, as with almost any base of data source there is a risk of hedge fund returns containing a variety of biases that could affect the empirical findings.

Hedge fund research has confirmed the existence of a positive relationship between volatility and fund disappearance (Ackermann, McEnally, & Ravenscraft, 1999). In general, when it comes to *survivorship biases* we usually distinguish between surviving funds and defunct funds. Whereas the surviving funds are still operating (alive) and present in the database as opposed to defunct funds that have left the database (Fung, W., & Hsieh, D.A., (2000), Malkiel, B., & Saha, A., (2005)). We are applying data from Eurekahedge, equal weighted index for Europe. In order to eliminate the effects of survivorship they track down the historical returns of funds that died and keep in the sample for the period they were alive as well as including funds that are closed for further capital inflows.

Fung and Hsieh (2000) claim that *selection biases* might occur when return data are not representative of the overall population, due to lack of regulations within the hedge fund industry. Edwards and Caglayan (2001) argue that the selection bias that is caused by the voluntary reporting might very well result in over- and underestimation of the hedge fund performance, possibly affecting the returns both positively and negatively. In contrast Fung and Hsieh (2000) argue that if the bias exists at all, it's probably very small.

Another potential bias, the so called *multi period sampling* bias refers to return history. Conducting empirical tests, it is of great importance to have reliable data in order to enable future predictions. To enable more accurate and reliable results from empirical testing, one needs sufficient return data. According to Ackermann, McEnally and Ravenscraft (1999) and in line with Edwards and Caglayan (2001) a minimum of 24 months of return history is required, although, Fung and Hsieh (2000) argue that the effect of the usage of shorter return histories is relatively small. Therefore we believe that 148 months (per hedge fund style) return data is sufficient in order overcome potential bias related to sample history.

4. EMPIRICAL RESULTS AND ANALYSIS

In the chapter we will present our empirical findings and analyze the results from the different asset pricing models. To begin with, we will discuss some descriptive statistics, followed by analysis of results which will be separated according to the different asset pricing models.

4.1 Descriptive Statistics

Before we start to investigate the performance of the hedge funds it is relevant to check for the explanatory statistics of the hedge fund returns data for all the 8 different investment strategies during the whole period.

In order to compare the hedge fund's performance with the equity market we found it appropriate to use S&P Europe 350 index as a proxy for the equity market since our data sample consists of hedge fund returns in Europe. During the whole period of investigation, the monthly average return for our sample hedge fund's data is 0.465% which is remarkably high compared to the monthly average return yielded by S&P Europe 350 index, -0.190% for the same period. As it can be seen by the comparison between the standard deviations, 0.024 with 0.05, the average systematic risk for the hedge fund returns is much lower than for the equity index. This is in contrast with our expectations about risk and return tradeoff since hedge fund returns show higher return simultaneously lower standard deviation than the well-diversified equity market index. Considering the data in the whole period, all the strategies yielded higher monthly average returns than the S&P Europe 350 index. The lowest performance is for the Arbitrage strategy while the Macro investment style shows the highest average return.

Strategies	Average return	Std.	Sharpe ratio	Skewness	Kurtosis	JB
Arbitrage	0,046	0,019	-0,075	0,591	7,958	396,50
CTA	0,396	0,014	0,146	-0,553	3,395	78,07
Event Driven	0,432	0,020	0,125	-0,197	6,402	251,95
Fixed Income	0,212	0,018	0,014	-1,798	6,578	344,30
Long Short Equities	0,509	0,022	0,148	0,075	3,253	64,96
Macro	1,073	0,059	0,151	-0,022	2,522	38,96
Multistrategy	0,683	0,028	0,177	1,261	8,429	474,09
Relative Value	0,373	0,020	0,092	2,954	18,298	2264,48
S&P Europe 350	-0,190	0,051	-7,441	-0,717	3,596	14,78
Average of all hedge funds	0,465	0,025	0,097	0,289	7,104	489,17

Table 4.1. *Data statistics for the whole period (December 1999 – March 2012).*

The Sharpe ratio is a measure of risk premium per each unit of risk and for all the strategies except for arbitrage, it outperforms the Sharpe ratio of the market equity index. The negative Sharpe ratio for the Arbitrage strategy can be explained by its lower expected return than risk free rate. According to this performance measure, we can conclude that the rational investor is expected to invest in hedge funds due to their higher Sharpe ratio.

For almost half of the investment styles the skewness is positive which is more preferable for the investors as it allows for gaining enormously high returns while at the same time limits the downsides. As the data statistics shows (Table 4.1), the excess kurtosis indicates leptokurtic distribution and the high Jarque-Bera test statistics for all the strategies following chi-two distribution, is an evidence for non-normal distributed hedge funds data since it goes beyond 5.99 the critical value at 5% significance level.

We divided the whole period into three different sub-periods (1999M12-2003M12, 2004M01-2007M12, 2008M01-2012M03). Except for the second sub-period, the hedge fund shows better performance than the equity market index. Among all the investment strategies, Macro in the first two sub-periods and event driven in the third one, show the highest return. The average return of the hedge funds in the sub-periods before the financial crisis exceeds the total period average (0.467%) while after the crisis sub-period's return is significantly lower. As the results shows (see Appendix, Table 7.1-3) the standard deviation in all the sub-periods is almost twice higher for the equity market index compared with the hedge fund returns. So it can be concluded that on average hedge funds face lower risk and in that case outperform the S&P Europe 350 index. In contrast with the theory underlying CAPM, in all the sub-periods but the one before the financial crisis, the lower risk followed by the higher return. Therefore one can conclude that considering risk and return, the hedge funds outperforms the market in both first and third sub-periods and it's much safer to invest in the average hedge funds rather than equity market. The higher Sharpe ratio for the well-diversified market index is also another proof for the lower performance of the hedge funds for the sub-period II. For almost half of the strategies, we can't reject the null hypothesis of normally distributed sample data in the second sub-period (lower JB test statistics than its critical value). Even though Jarque-Bera test results imply that the errors are not normally distributed we still assume that the estimators are consistent, which is in line with Brooks (2008).

Before we start to estimate the various equations, we also verify stationarity. We apply the ADF test type (see Appendix, Table 7.4) and the results find the data to be stationary as we

are able to reject the null. As we include intercept in our estimations we can be sure that $E(u_t)=0$ holds. Test results of the remaining OLS assumptions will be discussed below, in the end we believe that our parameters are BLUE, as the results and adjustments ensure the validity of inferences made.

4.1.1 Multicollinearity

	RM_RF	SMB	HML	MOM	MT	VIX	IPI
RM_RF	1						
SMB	0,312	1					
HML	-0,140	-0,384	1				
MOM	-0,349	0,145	-0,124	1			
MT	0,726	0,246	-0,128	-0,370	1		
VIX	0,020	0,032	-0,235	-0,184	0,268	1	
IPI	-0,165	-0,112	-0,121	0,017	-0,191	-0,138	1

Table 4.2. *Correlation between independent variables.*

As a way of checking for multicollinearity between the independent variables we simply examine the correlation matrix between each and one of variables. As discussed, a correlation coefficient higher than 80 percent is considered to demonstrate problems related to multicollinearity. Table 4.2, show that for all the independent variables the correlation doesn't exceed the critical value of 80 percent, suggesting that we don't have problems with multicollinearity.

4.2 CAPM

We are going to investigate whether the single beta unconditional asset pricing model, CAPM is able to explain the performance of the hedge fund returns as the first stage of our empirical research. As we mentioned before in the second chapter, we need to run the following model:

$$R_{it}-R_{ft} = \alpha_i + \beta_i (R_{mt}-R_{ft}) + \varepsilon_t$$

In order to be able to obtain reliable results we need to check for autocorrelation and heteroskedasticity before explaining the Jensen's alpha, CAPM beta and adjusted R-squared as a measure of the goodness of the fit. The Durbin-Watson test statistic checks for the existence of autocorrelation in the residuals. The value of the d-test statistic always lies between zero and four. To test for autocorrelation the d-value should be compared with the lower and higher critical values. The d=1 signifies no autocorrelation. So as a rule of thumb,

if the d-test statistic lies between one and three we can accept the absence of serial correlation between the error terms while the values below one and above three will be signs of positive- and negative autocorrelation respectively. Checking for the Durbin-Watson statistic for all the hedge funds strategies in all the periods, none of the values specify autocorrelation problem in our sample data. Moreover, with the aim of achieving BLUE coefficient estimates, we need to check if the variance of the residuals in the regression model is constant and in other words homoskedastic. White-test is used to test for the heteroskedasticity and the null hypothesis of homoskedasticity can't be rejected if the p-value is above 5% significant level. Considering the p-values of the White's F-statistics in all the periods, in the first period the fixed income strategy, in the second period the CTA strategy and in the last period fixed income and relative values strategies show the sign of heteroskedasticity with p-values lower than 5%. So as to deal with this problem, we run the OLS regressions again this time by using the heteroskedasticity robust standard errors. The results for Durbin-Watson test statistic and white's F-statistics for all the sub-periods are reported in the appendix (see Table 7.5).

CAPM Strategies	**Heteroskedasticity**		**Autocorrelation**
	F-statistic	**P-value**	**DW**
Arbitrage	0,30	0,58	1,06
CTA	1,95	0,16	1,73
Event Driven	24,38	0,00	1,51
Fixed Income	13,55	0,00	1,49
Long Short Equities	0,03	0,85	1,31
Macro	0,14	0,71	1,75
Multistrategy	0,07	0,79	1,49
Relative Value	0,10	0,75	1,25

Table 4.3. *Results for Heteroskedasticity and autocorrelation* for the entire period between December 1999 and March 2012.

4.2.1 Results and Analysis

The results for unconditional CAPM indicate that except for the last period, the majority of the hedge funds strategies provided abnormal returns throughout the investigation. During the whole period almost all the investment styles but arbitrage and fixed income, yielded positive excess returns with regard to their significant positive Jensen's alpha. In the first sub period, excluding Fixed Income, all the strategies show significant positive intercept at level of 5 percent. In the second sub period only three strategies gained positive abnormal returns whereas the Arbitrage strategy provided negative significant Jensen's alpha. Multi-strategies

as well as the Long Short equities are the ones which showed positive excess returns in both of these sub-periods. CTA is the only investment strategy which yielded positive anomalies during the last period after the financial crisis. It is worth mentioning that there is no evidence for the positive performance of any specific strategy in all sub periods.

CAPM Strategies	1999m12-2012m03				1999m12-2003m12			
	Intercept	**Beta**	**R2**	**Adj-R2**	**Intercept**	**Beta**	**R2**	**Adj-R2**
Arbitrage	0,033	0,097	0,065	0,059	0,616	0,033	0,009	-0,013
p-value	*0,83*	*0,002*			*0,029*	*0,523*		
CTA	0,387	0,067	0,055	0,048	0,795	0,096	0,086	0,066
p-value	*0,001*	*0,004*			*0,002*	*0,076*		
Event Driven	0,400	0,228	0,336	0,331	0,257	0,022	0,028	0,007
p-value	*0,024*	*0,000*			*0,014*	*0,252*		
Fixed Income	0,189	0,165	0,217	0,212	0,206	0,099	0,055	0,034
p-value	*0,264*	*0,000*			*0,527*	*0,109*		
Long Short Equities	0,467	0,298	0,465	0,461	0,831	0,24	0,338	0,324
p-value	*0,001*	*0,000*			*0,014*	*0,000*		
Macro	0,997	0,543	0,212	0,206	2,166	0,752	0,358	0,344
p-value	*0,022*	*0,000*			*0,009*	*0,000*		
Multistrategy	0,651	0,228	0,164	0,158	1,421	0,066	0,01	-0,012
p-value	*0,003*	*0,000*			*0,01*	*0,510*		
Relative Value	0,357	0,117	0,083	0,076	0,934	0,110	0,036	0,015
p-value	*0,028*	*0,000*			*0,043*	*0,196*		

Table 4.4. *Summarized CAPM results for the whole period and the first sub-period.*

CAPM Strategies	2004m01-2007m12				2008m01-2012m03			
	Intercept	**Beta**	**R2**	**Adj-R2**	**Intercept**	**Beta**	**R2**	**Adj-R2**
Arbitrage	-0,427	0,046	0,017	-0,005	-0,087	0,167	0,182	0,165
p-value	*0,002*	*0,384*			*0,784*	*0,002*		
CTA	0,095	0,004	0,000	-0,022	0,332	0,067	0,137	0,119
p-value	*0,674*	*0,969*			*0,032*	*0,008*		
Event Driven	0,207	0,328	0,339	0,325	0,517	0,360	0,562	0,552
p-value	*0,223*	*0,000*			*0,076*	*0,000*		
Fixed Income	0,045	0,157	0,199	0,182	0,268	0,216	0,511	0,501
p-value	*0,697*	*0,002*			*0,202*	*0,000*		
Long Short Equities	0,554	0,400	0,350	0,336	-0,043	0,331	0,680	0,673
p-value	*0,008*	*0,000*			*0,835*	*0,000*		
Macro	1,521	0,835	0,104	0,084	-0,613	0,368	0,332	0,318
p-value	*0,099*	*0,026*			*0,196*	*0,000*		
Multistrategy	0,738	0,314	0,267	0,252	-0,313	0,347	0,646	0,639
p-value	*0,000*	*0,000*			*0,179*	*0,000*		
Relative Value	0,17	0,130	0,169	0,151	-0,035	0,133	0,368	0,355
p-value	*0,116*	*0,004*			*0,836*	*0,004*		

Table 4.5. *Summarized CAPM results for the second and the third sub-periods.*

For the whole period as well as all the three sub-periods Macro strategy yielded the highest abnormal return, however for the last period the alpha is not significant. The observed alphas were not significant for Fixed Income strategy in any sub-period even at 10 percent significance level. The alphas vary across strategies from 0.2% to almost 2% throughout the different sub-periods. Event driven yielded the lowest abnormal return of 0.25 percent per month in the first period while the highest anomaly provided by Macro (2.16 percent) for the same duration of time.

It is logical to expect very low betas for hedge fund returns, since by definition the performance of these funds should be independent of the market movements. However, obtaining factor loadings close to zero is unlikely in reality. Except for the first sub-period, nearly all the betas are significant for all the investment styles. The beta differs from 0.066 for CTA in the last sub period to 0.83 for Macro in the second sub-period. Throughout the entire period the results didn't show any negative factor loadings for any of the strategies.

According to R^2 and adjusted-R^2, it seems that unconditional one factor asset pricing model, CAPM is incapable of explaining the performance of the hedge fund returns. The values for adjusted-R^2 vary from -0.021 for CTA in the second period to 0.673 for Long Short equities in the third period. It can be concluded that highest adjusted-R^2 is obtainable for strategies that are highly related to the equity market. However, in general low goodness of fit results indicates the poor explanatory power of the model. CAPM doesn't allow for inclusion of other risk factors in the model so is not appropriate to capture the variability of returns of the different of hedge funds.

4.3 Fama-French Three Factor Model

Secondly, we are interested in investigating another static model, named Fama-French three factor model which have proven to outperform CAPM as it additionally includes both size- and book-to-market risk factors. As presented in 2.6.2, we estimate the following equation:

$$R_i - R_f = \alpha_i + \beta_i(R_m - R_f) + \gamma_i \, SMB + \delta_i \, HML + \varepsilon_i$$

Whilst estimating the equation, tests results from the DW and White's-test implies that some regressions suffer from both autocorrelation and heteroskedasticity (see Table 4.6, Appendix: Table 7.6). Examining the Durbin-Watson statistics, we conclude that only arbitrage strategy, in the period between 1999M12 and 2003M12, demonstrate problems related to

autocorrelation. Investigating the results obtained by the White's tests, we find evidence for heteroskedasticity in the period between 1999M12 and 2003M12 as well as for the whole period since we reject the null of homoskedasticity. We adjust the data by employing the Newey-West estimator.

Fama-French Model Strategies	Heteroskedasticity		Autocorrelation
	F-statistic	P-value	DW
Arbitrage	24,97	0,00	1,08
CTA	0,74	0,53	1,79
Event Driven	5,76	0,00	1,56
Fixed Income	4,23	0,01	1,45
Long Short Equities	66,90	0,00	1,37
Macro	0,07	0,98	1,79
Multistrategy	1,01	0,39	1,52
Relative Value	106,93	0,00	1,24

Table 4.6. *Results for Heteroskedasticity and autocorrelation* for the entire period between December 1999 and March 2012.

4.3.1 Results and Analysis

The Fama-French regression output for the whole period (Table 4.7) recording significant (at 5%-level) positive alphas within 4 out of the 8 strategies, implying that the different alternative investment styles were able to "beat the market". For the additional periods, results show a declining number of significant alphas in both up- and down markets whereas 2, 3 and none significant alphas could be found for the first-, second- and third sub-periods, respectively (Table 4.7-8). The strategies exhibiting significant alphas were also identified as significant under the traditional asset pricing model. Regarding the alpha values, representing the performance, one can conclude that the excess return decrease under the Fama-French three factor model. A possible explanation of decreasing returns lies in the fact of additionally including the risk factors that slightly reduce the excess returns as it better can explain the variance. The significant alphas fluctuate and none of the strategies persistently exhibit positive abnormal returns throughout the different periods. Merely all significant beta values in the Fama-French three factor model were also shown to be significant under CAPM, except of the beta value for the CTA-strategy in the first sub-period . During the investigation the Event Driven-strategy displays the lowest significant market beta, except between 2004M01 and 2007M12, where Fixed-Income-strategy exhibit the lowest market beta. All the

significant betas were shown to be positively correlated with the overall market, regardless of the market condition.

Fama-French Model Strategies	1999m12-2012m3						1999m12-2003m12					
	Intercept	**Beta**	**Beta-SMB**	**Beta-HML**	**R2**	**Adj-R2**	**Intercept**	**Beta**	**Beta-SMB**	**Beta-HML**	**R2**	**Adj-R2**
Arbitrage	-0,015	0,085	0,068	0,037	0,081	0,061	0,727	-0,019	0,008	-0,103	0,074	0,011
p-value	*0,950*	*0,031*	*0,271*	*0,448*			*0,112*	*0,687*	*0,924*	*0,136*		
CTA	0,323	0,051	0,088	0,050	0,101	0,082	0,339	0,162	0,183	0,227	0,330	0,284
p-value	*0,006*	*0,033*	*0,009*	*0,140*			*0,173*	*0,002*	*0,001*	*0,001*		
Event Driven	0,332	0,226	0,046	0,094	0,362	0,349	0,123	0,039	0,056	0,064	0,165	0,109
p-value	*0,062*	*0,000*	*0,242*	*0,063*			*0,261*	*0,070*	*0,015*	*0,028*		
Fixed Income	0,134	0,150	0,081	0,040	0,242	0,226	-0,016	0,096	0,139	0,065	0,133	0,074
p-value	*0,442*	*0,001*	*0,023*	*0,354*			*0,964*	*0,174*	*0,065*	*0,490*		
Long Short Equities	0,405	0,271	0,125	0,018	0,504	0,494	0,715	0,196	0,134	-0,023	0,471	0,435
p-value	*0,005*	*0,000*	*0,062*	*0,650*			*0,033*	*0,000*	*0,046*	*0,707*		
Macro	0,927	0,493	0,207	-0,031	0,230	0,214	1,564	0,784	0,321	0,226	0,401	0,360
p-value	*0,037*	*0,000*	*0,107*	*0,808*			*0,085*	*0,000*	*0,085*	*0,333*		
Multistrategy	0,600	0,226	0,036	0,068	0,171	0,154	1,563	0,023	-0,025	-0,100	0,020	-0,047
p-value	*0,007*	*0,000*	*0,571*	*0,284*			*0,014*	*0,849*	*0,842*	*0,529*		
Relative Value	0,381	0,116	-0,009	-0,039	0,087	0,068	1,147	0,072	-0,076	-0,115	0,053	-0,011
p-value	*0,107*	*0,022*	*0,903*	*0,417*			*0,116*	*0,432*	*0,531*	*0,237*		

Table 4.7. *Summarized Fama-French results for the whole period and the first sub-period.*

Fama-French Model Strategies	2004m01-2007m12						2008m01-2012m03					
	Intercept	**Beta**	**Beta-SMB**	**Beta-HML**	**R2**	**Adj-R2**	**Intercept**	**Beta**	**Beta-SMB**	**Beta-HML**	**R2**	**Adj-R2**
Arbitrage	-0,481	0,047	0,025	0,160	0,111	0,051	-0,076	0,175	-0,031	-0,011	0,183	0,130
p-value	*0,001*	*0,470*	*0,731*	*0,039*			*0,821*	*0,008*	*0,832*	*0,928*		
CTA	0,143	-0,040	0,073	-0,047	0,012	-0,055	0,294	0,083	0,032	-0,099	0,197	0,144
p-value	*0,552*	*0,724*	*0,388*	*0,620*			*0,059*	*0,006*	*0,635*	*0,073*		
Event Driven	0,161	0,291	0,107	0,220	0,430	0,391	0,486	0,416	-0,046	-0,217	0,606	0,580
p-value	*0,342*	*0,001*	*0,253*	*0,025*			*0,093*	*0,000*	*0,714*	*0,037*		
Fixed Income	-0,072	0,211	-0,059	0,234	0,409	0,369	0,281	0,246	-0,070	-0,078	0,534	0,504
p-value	*0,505*	*0,000*	*0,319*	*0,000*			*0,182*	*0,000*	*0,315*	*0,296*		
Long Short Equities	0,530	0,322	0,189	0,247	0,452	0,415	-0,032	0,372	-0,085	-0,113	0,704	0,685
p-value	*0,011*	*0,002*	*0,090*	*0,032*			*0,878*	*0,000*	*0,358*	*0,127*		
Macro	1,386	0,628	0,538	0,873	0,179	0,123	-0,703	0,463	-0,019	-0,416	0,417	0,379
p-value	*0,144*	*0,172*	*0,299*	*0,104*			*0,132*	*0,000*	*0,925*	*0,014*		
Multistrategy	0,713	0,283	0,084	0,146	0,304	0,257	-0,291	0,407	-0,133	-0,159	0,691	0,671
p-value	*0,001*	*0,006*	*0,451*	*0,205*			*0,202*	*0,000*	*0,192*	*0,053*		
Relative Value	0,198	0,084	0,088	0,017	0,209	0,155	-0,099	0,166	0,043	-0,189	0,513	0,481
p-value	*0,083*	*0,126*	*0,156*	*0,785*			*0,521*	*0,000*	*0,387*	*0,000*		

Table 4.8. *Summarized Fama-French results for the second and the third sub-period.*

Most of the hedge funds have positive exposure to the size factors, however SMB coefficients are not significant, apart from CTA- and Fixed Income strategies in the first sub-period and CTA-, Event Driven- and Long Short Equity strategies in sub-period two, hence show positive factor loading which is in line with previous studies (Fama & French, 1993).

The estimated book-to-market factors imply that some of the HML coefficients are significant in period I, II and III. As value stocks impose higher risk, they should as a result generate higher returns (Fama & French, 1993). Consequently, we would expect positive HML factor loadings in up markets (period II) and negative in down markets (period III). The negative sign imply shifts towards growth stocks which can be observed in last period, which doesn't come as a surprise given the financial crisis. The motivation of the different signs comes from the fact that the market perceives the value stocks more risky over growth stocks (Table 4.7-8).

Before going further investigating the unconditional models we briefly need to compare and look at the explanatory power of the Fama-French factor model. The goodness-of-fit, R^2, indicates higher values of R^2 than the traditional one factor model, in all periods, ranging from 8,1 percent obtained by the Arbitrage-strategy to 50,4 percent obtained by the Long Short Equity strategy. We can for this reason conclude that the Fama-French factor model is better in explaining the abnormal return compared to the traditional one factor model. Given that hedge fund excess return variations are influenced by various risk factors, we will as a remedy consider the conditional factor model, accounting for time variability will increase the goodness-of-fit concerning the different strategies.

4.4 Conditional Factor Model

We extend our research in order to find more suitable model for explaining hedge fund risk exposure and check whether it is possible to observe positive and significant alphas by estimating the conditional Multi-factor model:

$$R_i\text{-}R_f = \alpha_{i0} + \beta_{i1}(R_m\text{-}R_f) + \beta_{i2}SMB + \beta_{i3}HML + \beta_{i4}MOM + \beta_{i5}MT + \beta_{i6}(VIX(R_m\text{-}R_f) + \beta_{i7}(IPI(R_m\text{-}R_f) + \beta_{i8}(VIX \cdot SMB) + \beta_{i9}(IPI \cdot SMB) + \beta_{i10}(VIX \cdot HML) + \beta_{i11}(IPI \cdot HML) + \beta_{i12}(VIX \cdot MOM) + \beta_{i13}(IPI \cdot MOM) + \beta_{i14}(VIX \cdot MT) + \beta_{i15}(IPI \cdot MT) + \varepsilon_i$$

Hence, we extend the Fama-French three factor model, by adding the supplementary risk factors, momentum and market timing. In addition we include instrumental variables that incorporate market's perception of risk, VIX, and the variable that stands as a proxy for the overall market situation, IPI.

According to the DW-statistics we can come to the conclusion that not any of the regressions, regarding any period, suffer from autocorrelation (Table 4.9, Appendix: Table 7.7). On the other hand, when it comes to problems related to heteroskedasticity, for the whole period the results of the White's test implies that Arbitrage-, Long-Short Equities and Relative value strategies suffer from heteroskedasticity, whereas Long-Short Equities also show problems in the first sub-period. We simply solve this problem by applying the Newey-West estimator and instead use the robust standard errors.

Multi Factor Model Strategies	**Heteroskedasticity**		**Autocorrelation**
	F-statistic	**P-value**	**DW**
Arbitrage	5,91	0,00	1,56
CTA	1,17	0,31	1,77
Event Driven	0,97	0,49	1,58
Fixed Income	0,53	0,92	1,45
Long Short Equities	30,37	0,00	1,39
Macro	1,50	0,11	1,97
Multistrategy	1,07	0,39	1,54
Relative Value	24,57	0,00	1,41

Table 4.9. *Results for Heteroskedasticity and autocorrelation* for the entire period between December 1999 and March 2012.

4.4.1 Result and Analysis

Under the Multi-factor model we find significant alphas for 3 out of the 8 strategies for the period between end of 1999 and March 2012 and the first sub-period. For the second sub-period we find positive significant alphas for 2 of 8 strategies and 1 of 8 for the last sub-period implying that the majority of the alphas demonstrate non significance regardless of period. Results reveal abnormal results ranging between -0.23% and 0.62% per month. Since only 1 out of the 8 strategies demonstrate a negative insignificant alpha, we believe that hedge funds as an alternative investment vehicle are able to hedge returns as results signify positive alphas for the majority of the strategies (although some of them are insignificant). This implies that they are able to generate positive excess returns in both up- and down markets.

Macro strategy demonstrates the highest significant abnormal return and also shows the highest average return (Table 4.1) between December 1999 and March 2012, we consequently believe that it is beneficial to invest in this hedge fund strategy.

Multi-Factor Model Strategies	1999M12 -2012M03							
	Intercept	**Beta**	**Beta-SMB**	**Beta-HML**	**Beta-MOM**	**Beta-MT**	**R2**	**Adj-R2**
Arbitrage	-0,227	-3,414	0,740	-2,117	-0,660	6,948	0,327	0,249
p-value	*0,437*	*0,000*	*0,631*	*0,035*	*0,343*	*0,002*		
CTA	0,528	-0,076	1,802	2,307	-0,838	0,084	0,243	0,157
p-value	*0,012*	*0,896*	*0,033*	*0,016*	*0,111*	*0,940*		
Event Driven	0,220	-2,467	1,627	2,194	0,244	1,107	0,538	0,485
p-value	*0,322*	*0,000*	*0,071*	*0,031*	*0,664*	*0,349*		
Fixed Income	0,322	-1,649	1,263	-0,154	0,167	1,784	0,361	0,288
p-value	*0,173*	*0,014*	*0,185*	*0,885*	*0,778*	*0,155*		
Long Short Equities	0,483	-1,410	2,600	-0,071	-0,733	2,439	0,596	0,550
p-value	*0,028*	*0,034*	*0,021*	*0,945*	*0,258*	*0,102*		
Macro	2,341	0,117	2,842	-0,098	-2,418	3,891	0,363	0,290
p-value	*0,003*	*0,958*	*0,368*	*0,978*	*0,222*	*0,350*		
Multistrategy	0,621	-3,502	-0,233	1,068	-1,343	3,783	0,257	0,171
p-value	*0,125*	*0,002*	*0,886*	*0,561*	*0,189*	*0,079*		
Relative Value	0,287	-1,203	-1,345	0,558	1,161	4,059	0,226	0,138
p-value	*0,268*	*0,070*	*0,388*	*0,606*	*0,184*	*0,135*		

Table 4.10. *Summarized Fama-French results for the entire period, December 1999 – March 2012.*

The market factor (R_m-R_f) observed for the various hedge funds, are significant (at 5% significance level) in five cases (Table 4.10), where all are negative and imply that hedge fund returns have a negative sensitivity towards the market movements and results show negative significant betas for all the periods except for the second sub-period (see Appendix: Table 7.9-11). Theories suggests that in both way, hedge funds should enable positive returns no matter market situation and as more the model is able to explain the variance, the results of the market factor will tend towards 0.

The outcome referring to the negative and positive size factor loadings indicate that there are strategies that take short positions and long position in small capital stocks respectively. Hence, it's evident that fund managers prefer small (large) caps over large (small) caps when we have positive (negative) factor loadings for the SMB. The results show that the IT-bubble did generate one negative size factor loadings for the arbitrage strategy, compared to results given during- and after the real estate crisis. (see Appendix: Table 7.9-11)

Three out of the eight HML coefficients are significant (Table 4.10), whereas two of the strategies show positive factor loadings. We cannot therefore explain whether hedge funds are exposed to value risk and if preferences lean towards growth stocks, since only two of the all show positive factor loadings.

Data sample stretching between December 1999 and March 2012 show that none of strategies demonstrate significant momentum beta. Referring to period I and II we find that 1 and for period III, 3 out of 8 strategies respectively show significant betas. On the other hand the sign does vary, where the majority of the strategies show negative significant betas for the period II and III, implying that momentum cannot be considered as a compensation of bearing an extra risk, i.e. momentum can't explain the abnormal returns.

Regarding the market timing ability, MT, the results show that only one out of all the strategies (Arbitrage) in the whole period shows significant coefficient value while we get positive significant betas for 3 and 2 of the strategies for the first and third sub-periods respectively (see Table 4.10, Appendix: Table 7.9-11). The existence of positive market timing ability is in line with Chen and Liang (2007). Meaning that, hedge fund managers in deed are able to earn higher abnormal returns when the market is expected to rise, which is in line with Gupta et al. (2003). However, according to our findings the small number of significant coefficients implies that this cannot be verified.

The conditional effects in Table 7.8 (see Appendix) shows that the ($IPI \cdot R_m$-R_f) is positive and for the majority also significant. This implies that the market factor is higher in bear markets, i.e. the hedge funds will follow the market more in up markets and less in down markets, which seems logical. For the other conditional effects, a minor part of the betas are not significant and for this reason we are not able to explain the various conditioning effects.

The goodness-of-fit, R^2 and the adjusted-R^2 of the conditional Multi-factor model indicates that the explanatory power is significantly higher than for both CAPM and Fama-French three factor model. The explanatory power has consistently risen, varying from 22% and 60%, the results proves that the conditional Multi-factor model, including both additional risk factors and instrumental variables provides the best fit compared to the static models, as it significantly and consistent contribute to the models explanatory power.

5. CONCLUSION

In this last chapter we will summarize our main findings in addition we will bring a suggestion for a potential further research.

The purpose of this paper has been to examine whether it is possible to obtain abnormal returns with various European hedge fund strategies during the period between December 1999 and March 2012 and to identify the potential risk factors affecting the returns. In line with previous studies on the performance of hedge fund, we applied unconditional CAPM, Fama-French three factor model and a conditional time varying Multi-factor model. Jensen's alpha and Sharpe ratio have been used as measures of the performance.

CAPM	**Sign. Alpha**	**Average alpha**	**Average R2**	**Average adj. R2**
Whole period	6	0,435	0,199	0,194
Sub-period I	7	0,903	0,115	0,096
Sub-period II	3	0,363	0,181	0,163
Sub-period III	2	0,003	0,427	0,415
Fama-French Model	**Sign. Alpha**	**Average alpha**	**Average R2**	**Average adj. R2**
Whole period	4	0,386	0,222	0,206
Sub-period I	2	0,170	0,206	0,152
Sub-period II	3	0,322	0,263	0,213
Sub-period III	0	-0,017	0,481	0,447
Multi-Factor Model	**Sign. Alpha**	**Average alpha**	**Average R2**	**Average adj. R2**
Whole period	3	0,572	0,364	0,291
Sub-period I	3	1,132	0,542	0,327
Sub-period II	2	0,403	0,513	0,284
Sub-period III	1	0,227	0,713	0,59

Table 5.1 *Comparison between the three different model estimations.*

According to the table, the summary of results show that some of the hedge fund investment styles produce abnormal returns considering their significant alphas. This is similar to the findings of Liang (1999), Edwards and Caglayan (2001) and Kat and Miffre (2003). Higher Sharpe ratios for hedge fund returns compared with the Sharpe ratio of the market equity index for most periods is also a proof of the fact that hedge funds can beat the market and produce abnormal returns even though it varies among time and strategies. It is also evident that the number of significant alphas obtained from the various models change over time. A

possible explanation could be due to the fact that manager's ability to earn hedge fund returns differs among various business cycles.

The goodness-of-fit consistently rise as we include additional explanatory variables to the model, which was expected. R^2 and adjusted-R^2 show lower values for the CAPM and Fama-French compared to the conditional Multi-factor model. Hence, both models appear to be inappropriate to capture the performance of hedge funds as they are not able to explain the dynamic risk exposures. Even thought the average goodness-of-fit of the conditional model is not as high as we expected, it is still higher than 35 percent reported by Kat and Miffre (2003). Another explanation of the poor goodness-of-fit can be attributed to the number of explanatory variables and including insufficient risk factors.

5.1 Further studies

We believe that it could be a matter of interest to include supplementary risk factors as well as instrumental variables as a proxy for the business cycles in order to enhance the explanation power of the Multi-factor model. Furthermore, including other strategies as well as a more specified group of countries such as eastern or western European countries would be relevant to explore the existence of abnormal returns in the European markets.

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7. APPENDIX

Strategies	Average	Std.	Sharpe ratio	Skewness	Kurtosis	JB
Arbitrage	0,600	0,019	0,185	2,659	12,612	241,34
CTA	0,748	0,018	0,280	-1,251	7,806	58,72
Event Driven	0,246	0,007	-0,010	-0,850	3,968	7,66
Fixed Income	0,157	0,023	-0,042	-1,523	6,616	44,71
Long Short Equities	0,712	0,022	0,206	1,646	9,306	101,19
Macro	1,794	0,068	0,227	-0,364	2,376	1,84
Multistrategy	1,388	0,036	0,313	2,025	9,182	109,25
Relative Value	0,879	0,031	0,201	2,264	9,842	134,65
S&P Europe 350	-0,864	0,057	-0,195	-0,409	2,618	1,63
Average of all hedge funds	0,816	0,028	0,170	0,576	7,714	87,42

Table 7.1 *Data statistics, first sub-period (December 1999 – December 2003)*

Strategies	Average	Std.	Sharpe ratio	Skewness	Kurtosis	JB
Arbitrage	-0,399	0,009	-0,779	-0,710	5,775	19,43
CTA	0,098	0,013	-0,141	0,229	3,514	0,95
Event Driven	0,409	0,014	0,095	-1,051	4,050	11,05
Fixed Income	0,142	0,009	-0,159	-1,028	4,082	10,79
Long Short Equities	0,800	0,016	0,316	-0,630	3,089	3,19
Macro	2,035	0,063	0,278	0,849	4,447	9,95
Multistrategy	1,931	0,015	1,117	-0,145	3,332	0,39
Relative Value	0,250	0,008	-0,038	0,839	3,354	5,88
S&P Europe 350	0,972	0,026	0,265	-0,584	2,437	3,36
Average of all hedge funds	0,658	0,018	0,086	-0,206	3,955	7,70

Table 7.2 *Data statistics, second sub-period (January 2004 – December 2007)*

Strategies	Average	Std.	Sharpe ratio	Skewness	Kurtosis	JB
Arbitrage	-0,056	0,024	-0,038	-0,497	6,165	23,38
CTA	0,345	0,011	0,278	-0,208	2,905	0,39
Event Driven	0,629	0,030	0,199	-0,245	5,018	9,17
Fixed Income	0,330	0,019	0,157	-1,852	8,755	99,51
Long Short Equities	0,042	0,025	0,003	-0,544	3,572	3,21
Macro	-0,510	0,040	-0,138	-3,774	21,737	867,11
Multistrategy	-0,214	0,027	-0,093	-0,821	3,770	6,99
Relative Value	0,012	0,014	-0,017	-1,679	7,182	61,13
S&P Europe 350	-0,649	0,060	-0,114	-0,483	2,915	2,00
Average of all hedge funds	0,072	0,024	0,044	-1,202	7,388	133,86

Table 7.3 *Data statistics, third sub-period (January 2008 – March 2012)*

ADF-test	t-tatistic	Prob
ri_rf_arb	-6,81	0,00
ri_rf_cta	-10,90	0,00
ri_rf_eve	-7,75	0,00
ri_rf_fix	-8,44	0,00
ri_rf_lon	-8,06	0,00
ri_rf_mac	-9,89	0,00
ri_rf_mul	-5,46	0,00
ri_rf_rel	-8,66	0,00
rm_rf	-10,37	0,00
SMB	-14,08	0,00
HML	-11,32	0,00
MOM	-11,67	0,00
MT	-11,62	0,00
VIX_rm_rf	-10,49	0,00
IPI_rm_rf	-10,16	0,00
VIX_SMB	-14,59	0,00
IPI_SMB	-14,03	0,00
VIX_HML	-10,71	0,00
IPI_HML	-11,13	0,00
VIX_MOM	-7,03	0,00
IPI_MOM	-11,57	0,00
VIX_MT	-10,20	0,00
IPI_MT	-11,57	0,00
S&P	-10,16	0,00

Table 7.4 *Augmented Dickey-Fuller test for non-stationarity.*

CAPM Strategies	1999m12-2003m12			2004m01-2007m12			2008m01-2012m03		
	Heteroskedasticity		Autocorrelation	Heteroskedasticity		Autocorrelation	Heteroskedasticity		Autocorrelation
	F-statistic	P-value	DW	F-statistic	P-value	DW	F-statistic	P-value	DW
Arbitrage	0,67	0,42	1,04	1,91	0,17	1,50	0,14	0,71	1,31
CTA	3,57	0,07	1,75	7,70	0,01	1,64	1,43	0,24	1,82
Event Driven	1,18	0,28	1,51	0,69	0,41	1,48	1,52	0,22	1,79
Fixed Income	0,12	0,73	1,38	0,00	0,99	1,40	37,92	0,00	2,00
Long Short Equities	0,51	0,48	1,00	0,78	0,38	1,47	0,17	0,68	1,92
Macro	0,21	0,65	1,91	0,01	0,93	1,78	1,66	0,20	1,96
Multistrategy	0,95	0,33	1,56	1,45	0,24	1,94	0,19	0,67	2,01
Relative Value	0,51	0,48	1,27	0,01	0,94	1,52	28,49	0,00	1,59

Table 7.5 *Results for Heteroskedasticity and autocorrelation for CAPM.*

Fama-French Model Strategies	1999m12-2003m12			2004m01-2007m12			2008m01-2012m03		
	Heteroskedasticity		Autocorrelation	Heteroskedasticity		Autocorrelation	Heteroskedasticity		Autocorrelation
	F-statistic	P-value	DW	F-statistic	P-value	DW	F-statistic	P-value	DW
Arbitrage	95,63	0,00	0,94	0,78	0,51	1,74	0,62	0,61	1,30
CTA	1,29	0,29	1,87	3,12	0,04	1,66	1,20	0,32	1,94
Event Driven	0,76	0,52	1,64	1,05	0,38	1,76	1,08	0,37	1,68
Fixed Income	0,05	0,99	1,17	1,35	0,27	1,68	11,35	0,00	1,93
Long Short Equities	92,43	0,00	1,02	0,37	0,78	1,71	0,29	0,83	1,86
Macro	0,27	0,85	2,04	1,79	0,16	1,89	1,59	0,21	1,99
Multistrategy	0,49	0,69	1,57	0,47	0,71	2,01	0,24	0,86	1,90
Relative Value	37,74	0,00	1,29	1,38	0,26	1,56	7,65	0,00	1,59

Table 7.6 *Results for Heteroskedasticity and autocorrelation, Fama-French Factor Model.*

Multi-Factor Model Strategies	1999m12-2003m12			2004m01-2007m12			2008m01-2012m03		
	Heteroskedasticity		Autocorrelation	Heteroskedasticity		Autocorrelation	Heteroskedasticity		Autocorrelation
	F-statistic	P-value	DW	F-statistic	P-value	DW	F-statistic	P-value	DW
Arbitrage	1,80	0,08	2,07	1,16	0,35	1,80	0,78	0,69	1,70
CTA	0,73	0,74	1,94	0,84	0,63	1,91	0,65	0,81	1,91
Event Driven	0,31	0,99	2,21	0,51	0,92	1,62	0,53	0,91	2,09
Fixed Income	0,75	0,71	1,42	0,87	0,60	1,44	0,36	0,98	1,88
Long Short Equities	3,60	0,00	1,26	0,60	0,85	1,81	0,38	0,98	2,05
Macro	0,57	0,88	2,06	1,81	0,08	2,03	3,57	0,00	1,41
Multistrategy	1,03	0,46	1,33	0,78	0,69	2,16	0,30	0,99	1,89
Relative Value	0,69	0,78	1,62	1,19	0,33	1,37	0,14	1,00	1,83

Table 7.7 *Results for Heteroskedasticity and autocorrelation, Multi-Factor Model.*

Strategies	α	β (Rm_Rf)	β (SMB)	β (HML)	β (MOM)	β (MT)	β (VIX-Rm_Rf)	β (IPI-Rm_Rf)	β (VIX-SMB)	β (IPI-SMB)	β (VIX-HML)	β (IPI-HML)	β (VIX-MOM)	β (IPI-MOM)	β (VIX-MT)	β (IPI-MT)	R2	Adj-R2
Arbitrage	-0,227	-3,414	0,740	-2,117	-0,660	6,948	0,006	0,033	0,002	-0,008	-0,004	0,023	0,006	0,005	-0,009	-0,066	0,327	0,249
p-value	0,437	0,000	0,631	0,035	0,343	0,002	0,098	0,000	0,825	0,587	0,225	0,026	0,003	0,505	0,122	0,003		
CTA	0,528	-0,076	1,802	2,307	-0,838	0,084	0,002	0,001	-0,005	-0,016	0,001	-0,023	-0,002	0,009	0,007	-0,004	0,243	0,157
p-value	0,012	0,896	0,033	0,016	0,111	0,940	0,618	0,820	0,278	0,061	0,789	0,020	0,459	0,089	0,185	0,691		
Event Driven	0,220	-2,467	1,627	2,194	0,244	1,107	-0,010	0,030	-0,007	-0,014	0,001	-0,022	-0,006	-0,001	0,005	-0,012	0,538	0,485
p-value	0,322	0,000	0,071	0,031	0,664	0,349	0,017	0,000	0,111	0,120	0,760	0,039	0,016	0,895	0,368	0,310		
Fixed Income	0,322	-1,649	1,263	-0,154	0,167	1,784	-0,010	0,022	0,002	-0,013	-0,007	0,004	0,000	-0,002	0,010	-0,022	0,361	0,288
p-value	0,173	0,014	0,185	0,885	0,778	0,155	0,020	0,001	0,746	0,182	0,086	0,690	0,968	0,741	0,073	0,080		
Long Short Equities	0,483	-1,410	2,600	-0,071	-0,733	2,439	-0,011	0,021	0,001	-0,026	-0,004	0,003	-0,006	0,009	0,004	-0,027	0,596	0,550
p-value	0,028	0,034	0,021	0,945	0,258	0,102	0,001	0,001	0,861	0,021	0,283	0,814	0,064	0,170	0,180	0,075		
Macro	2,341	0,117	2,842	-0,098	-2,418	3,891	-0,036	0,020	-0,016	-0,022	-0,025	0,010	-0,020	0,031	0,027	-0,058	0,363	0,290
p-value	0,003	0,958	0,368	0,978	0,222	0,350	0,012	0,367	0,314	0,481	0,083	0,792	0,029	0,118	0,158	0,170		
Multistrategy	0,621	-3,502	-0,233	1,068	-1,343	3,783	-0,001	0,038	0,001	0,003	-0,005	-0,009	-0,001	0,014	-0,001	-0,038	0,257	0,171
p-value	0,125	0,002	0,886	0,561	0,189	0,079	0,885	0,001	0,948	0,851	0,514	0,625	0,757	0,168	0,879	0,081		
Relative Value	0,287	-1,203	-1,345	0,558	1,161	4,059	0,005	0,012	-0,002	0,014	-0,001	-0,007	-0,003	-0,010	-0,010	-0,038	0,226	0,138
p-value	0,268	0,070	0,388	0,606	0,184	0,135	0,116	0,063	0,863	0,339	0,765	0,563	0,239	0,240	0,027	0,160		

Table 7.8.*Full conditional regression output for the entire period.*

Multi-Factor Model Strategies	1999M12 -2003M12							
	Intercept	**Beta**	**Beta-SMB**	**Beta-HML**	**Beta-MOM**	**Beta-MT**	**R2**	**Adj-R2**
Arbitrage	0,048	-1,936	-9,023	-1,886	2,469	4,068	0,633	0,461
p-value	*0,912*	*0,000*	*0,012*	*0,002*	*0,549*	*0,005*		
CTA	1,020	-1,861	-1,091	-1,567	5,271	1,493	0,609	0,425
p-value	*0,023*	*0,012*	*0,071*	*0,061*	*0,261*	*0,054*		
Event Driven	0,203	-4,124	-3,092	-5,530	2,283	7,252	0,511	0,282
p-value	*0,291*	*0,190*	*0,241*	*0,132*	*0,271*	*0,036*		
Fixed Income	0,075	1,869	-7,366	0,753	1,857	-2,041	0,491	0,252
p-value	*0,906*	*0,076*	*0,396*	*0,950*	*0,010*	*0,072*		
Long Short Equities	0,859	6,104	6,588	7,581	0,730	1,708	0,690	0,545
p-value	*0,002*	*0,568*	*0,148*	*0,201*	*0,891*	*0,250*		
Macro	4,092	5,424	5,145	9,622	1,381	-3,351	0,581	0,384
p-value	*0,021*	*0,058*	*0,826*	*0,766*	*0,455*	*0,268*		
Multistrategy	1,641	-2,050	-1,433	1,387	-0,152	5,223	0,177	-0,208
p-value	*0,205*	*0,922*	*0,416*	*0,954*	*0,991*	*0,816*		
Relative Value	1,121	1,191	1,391	2,033	3,332	4,637	0,644	0,477
p-value	*0,128*	*0,317*	*0,889*	*0,882*	*0,671*	*0,001*		

Table 7.9 *Summarized Multi-Factor results for the entire period, December 1999 – December 2003.*

Multi-Factor Model Strategies	2004M01 -2007M12							
	Intercept	**Beta**	**Beta-SMB**	**Beta-HML**	**Beta-MOM**	**Beta-MT**	**R2**	**Adj-R2**
Arbitrage	-0,475	-2,032	1,592	-4,674	-1,082	-0,132	0,444	0,183
p-value	*0,069*	*0,463*	*0,628*	*0,126*	*0,551*	*0,972*		
CTA	-0,245	5,060	4,607	-3,929	-3,143	-2,282	0,329	0,015
p-value	*0,553*	*0,262*	*0,388*	*0,420*	*0,287*	*0,708*		
Event Driven	0,467	0,848	1,551	-2,650	-4,210	-5,962	0,708	0,571
p-value	*0,114*	*0,788*	*0,678*	*0,440*	*0,048*	*0,171*		
Fixed Income	0,062	-1,268	0,582	2,106	-1,888	0,239	0,606	0,421
p-value	*0,771*	*0,581*	*0,831*	*0,400*	*0,215*	*0,939*		
Long Short Equities	0,885	3,625	1,346	-0,608	-0,338	-4,006	0,682	0,533
p-value	*0,020*	*0,362*	*0,774*	*0,887*	*0,896*	*0,459*		
Macro	1,341	1,568	-9,002	1,585	7,839	3,918	0,408	0,131
p-value	*0,484*	*0,450*	*0,714*	*0,482*	*0,564*	*0,890*		
Multistrategy	1,203	-0,496	4,881	-0,014	0,771	0,769	0,492	0,254
p-value	*0,006*	*0,912*	*0,362*	*0,998*	*0,793*	*0,900*		
Relative Value	-0,017	0,520	-1,933	-1,297	-1,079	-1,555	0,431	0,165
p-value	*0,939*	*0,833*	*0,511*	*0,629*	*0,506*	*0,645*		

Table 7.10 *Summarized Multi-Factor results for the entire period, January 2004 – December 2007.*

Multi-Factor Model Strategies	2008M01 -20012M03							
	Intercept	**Beta**	**Beta-SMB**	**Beta-HML**	**Beta-MOM**	**Beta-MT**	**R2**	**Adj-R2**
Arbitrage	0,065	-1,168	1,284	0,152	-1,186	2,867	0,510	0,300
p-value	*0,917*	*0,493*	*0,588*	*0,959*	*0,415*	*0,254*		
CTA	0,223	-0,415	0,598	0,962	-0,547	0,041	0,486	0,265
p-value	*0,451*	*0,605*	*0,593*	*0,494*	*0,425*	*0,972*		
Event Driven	0,644	-0,871	2,948	1,415	-2,415	1,454	0,814	0,735
p-value	*0,178*	*0,499*	*0,106*	*0,529*	*0,033*	*0,442*		
Fixed Income	0,737	-2,269	1,409	0,248	-1,194	2,625	0,823	0,748
p-value	*0,015*	*0,006*	*0,204*	*0,857*	*0,082*	*0,028*		
Long Short Equities	0,023	-0,263	1,664	0,669	-2,932	1,140	0,859	0,798
p-value	*0,948*	*0,779*	*0,207*	*0,683*	*0,001*	*0,408*		
Macro	0,177	-3,999	-1,782	4,511	-2,258	4,951	0,708	0,583
p-value	*0,787*	*0,073*	*0,527*	*0,373*	*0,120*	*0,049*		
Multistrategy	-0,084	0,158	0,082	-1,431	-2,894	0,775	0,798	0,711
p-value	*0,849*	*0,895*	*0,961*	*0,497*	*0,007*	*0,661*		
Relative Value	0,035	-0,896	-0,132	0,614	-0,954	0,604	0,706	0,580
p-value	*0,898*	*0,230*	*0,898*	*0,634*	*0,136*	*0,578*		

Table 7.11 *Summarized Multi-Factor results for the entire period, January 2008 – March 2012.*