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HEDGE FUNDS PERFORMANCE EVALUATION, A PORTFOLIO CONSTRUCTION AND APPLICATIONS

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ΔΙΑΤΡΙΒΗ

Που υποβλήθηκε στο Τμήμα Στατιστικής

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DEDICATION

Στην οικογένεια μου

To my family

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I would like to thank my supervisor Ioannis Vrontos, for accepting me as one of his students and helping me accomplishing this thesis. I would also like to thank my family for their substantial support.

VITA

I was born in Athens in 1979. In 1997, I graduated from the 1st High School of Ag.Anargiri, in Athens. In 2000, I entered the Department of Aquaculture and Fisheries, of Technological Educational Institute of Messolonghi. I graduated four years later, with grade 'very good'. In 2004 (plus one year of preparative cycle), I was accepted by the Master of Science Program in Statistics, of the Department of Statistics, in Athens University of Economics and Business. My scientific interests are Computational Statistics, Time Series Modeling and Generalized Linear Models.

ABSTRACT

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Hedge funds performance evaluation,
A portfolio construction and Applications

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We evaluate performance of hedge funds in order to construct top decile portfolios. In our study, we have the monthly returns of ten hedge funds and the monthly returns of fourteen market indices. We apply four different models for each hedge fund. The data from the last year of each hedge fund is used in the out-of-sample analysis. From each model, we receive the best two performing hedge funds. Consequently, we construct four different portfolios. The first kind of model is the single factor, the second is the three-factor of Fama and French (1993) and the third is the four-factor model of Carhart (1997). The fourth kind is a multifactor model. We use a backward selection approach in order to identify a suitable set of market indices for each hedge fund.

In the following, the models, which we have described above, are reused, applying Generalized Autoregressive Conditional Heteroskedasticity GARCH(1,1) models in order to capture the conditional heteroskedasticity or volatility clustering. Specifically, GARCH(1,1) models describe the conditional variances and covariances of financial time series. Therefore, we construct another four portfolios. Using some measures of risk, we compare these eight portfolios and we conclude by choosing the best top decile portfolio.

ΠΕΡΙΛΗΨΗ

Σωτήριος Δημητρακόπουλος

Αποτίμηση των κεφαλαίων αντιστάθμισης κινδύνων, Κατασκευή χαρτοφυλακίου και εφαρμογές

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Η αποτίμηση της απόδοσης των κεφαλαίων αντιστάθμισης κινδύνου και η κατασκευή top deciles χαρτοφυλακίων είναι ο αντικειμενικός σκοπός αυτής της εργασίας. Έχουμε στη διάθεσή μας, τις μηνιαίες επιστροφές δέκα κεφαλαίων αντιστάθμισης κινδύνου και τις μηνιαίες επιστροφές δεκατεσσάρων χρηματιστηριακών δεικτών. Εφαρμόζουμε τέσσερα διαφορετικά μοντέλα για κάθε ένα από τα δέκα κεφάλαια. Από την εφαρμογή κάθε μοντέλου, για το σύνολο των δέκα κεφαλαίων, λαμβάνουμε τα δύο καλύτερα από πλευράς απόδοσης. Συνεπώς, κατασκευάζουμε τέσσερα διαφορετικά χαρτοφυλάκια. Το πρώτο μοντέλο που εφαρμόζουμε περιλαμβάνει ένα παράγοντα. Το δεύτερο είναι το μοντέλο των Fama και French (1993). Το τρίτο είναι του Carhart (1997). Το τελευταίο μοντέλο περιλαμβάνει όλους τους χρηματιστηριακούς δείκτες για κάθε κεφάλαιο αντιστάθμισης κινδύνου. Με τη μέθοδο επιλογής κατάλληλων μεταβλητών backward καταλήγουμε σε μοντέλα ικανότερα από πλευράς ερμηνείας της διακύμανσης.

Εν συνεχεία, επαναχρησιμοποιούμε τα προαναφερθέντα μοντέλα, εφαρμόζοντας τα γενικευμένα αυτοπαλίνδρομα μοντέλα υπό συνθήκη ετεροσκεδαστικότητας GARCH(1,1), με σκοπό να περιγράψουμε τις δεσμευμένες διακυμάνσεις και συνδιακυμάνσεις των χρηματοοικονομικών χρονολογικών σειρών. Επομένως, κατασκευάζουμε άλλα τέσσερα χαρτοφυλάκια. Στο τελευταίο σκέλος της εργασίας εφαρμόζουμε διάφορα μέτρα υπολογισμού του κινδύνου και της λειτουργίας κάθε χαρτοφυλακίου με σκοπό να καταλήξουμε στο καλύτερο μοντέλο από πλευράς απόδοσης.

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CHAPTER ONE

INTRODUCTION

1.1 Hedge funds historical review, definition and strategies

Alfred Jones was the father of hedge funds. He was American and he graduated from Harvard in 1923 and became a U.S diplomat in the beginning of the decade of 1930 in Berlin, Germany. He studied sociology in Columbia University and joined the editorial staff at Fortune magazine.

In 1948 he raised \$100.000 (\$40.000 his own) and he tried to minimize the risk in holding long-term stock positions by short-selling other stocks. For the first time in history, we watched the classic long/short equity investing model. He also employed leverage to enhance returns. In 1952, he caused a change in the structure of his investment vehicle, converting it from a general partnership to a limited partnership. Specifically, before Alfred Jones proceeded to this change, partners had unlimited liability, which means that their personal assets were liable to the partnership's obligation. Nowadays, one or more of the partners is liable only to the extent of the amount of money that partner has invested. Namely, the owners are generally not liable for the debts of the company. He, also, introduced the incentive fee as compensation for the manager with the prospect that the manager will surpass a concrete limit of profits (watermark). In this historical frame hedge funds were created and developed.

Hedge funds are lightly regulated private investment funds that use unconventional investment strategies and tax shelters in an attempt to make extraordinary returns in any market. We refer to "lightly regulated" because in 2004 the Securities and Exchange Commission (SEC) (which is a government commission created by the Congress to regulate securities markets and protect investors) adopted changes that require hedge fund managers and sponsors to register as investment advisors under the Investment Advisor's Act of 1940. Some of the requirements are concerned to keep up-to-date performance records, hiring a compliance officer and creating a code of ethics. These actions are become to protect investors from the speculators. In addition, we must refer that there are two types of hedge funds. U.S (onshore) and offshore hedge funds. U.S hedge funds are limited partnerships. Offshore funds are limited liability corporations or partnerships established in tax neutral jurisdictions that allow investors an opportunity to invest outside their own country and minimize their tax liabilities. Finally, offshore funds are more flexible than onshore funds because they offer more privacy, enjoy certain tax advantages and are not restricted as to the number of investors.

We have accomplished the definition of hedge funds. Now, we must add that all hedge funds are not the same, because they use different strategies, in which investment returns, volatility and risk vary enormously. Hedge fund strategies tend to hedge against downturns in the markets being traded.

1.2 Hedge fund strategies

Hedge funds are flexible in their investment options (can use short selling, leverage, derivatives such as puts, calls, options, futures, etc). Hedge funds benefit by heavily weighting hedge fund managers' remuneration towards performance incentives, thus attracting the best brains in the investment business. It is commonly known that hedge fund managers are generally highly professional, disciplined and diligent. Investing in hedge funds tends to be favored by more sophisticated investors, including many Swiss and other private banks, which have lived through, and understand the consequences of major stock market corrections. Many endowments and pension funds allocate assets to hedge funds. Nowadays, hedge funds are estimated to be a trillion dollar industry with about 8350 active hedge funds. In the following, we present the main categories of hedge fund strategies.

Convertible Arbitrage: Purchase a portfolio of convertible securities, generally convertible bonds, and hedge a portion of the equity risk by selling short the underlying common stock. Most managers employ leverage, and the equity hedge ratio may range from 30% to 100%.

Distressed Securities: Invest in, and may sell short, the securities of companies whose security prices have been, or are expected to be, affected by a distressed situation such as a bankruptcy, distressed sale, or other corporate restructuring. Depending on the manager's style, investments may be in bank debt, corporate debt, trade claims, common stock, preferred stock, and warrants.

Emerging Markets: Invest in sovereign or corporate securities of developing or "emerging" countries. Investments are primarily long.

Equity Hedge: Consists of a core holding of long equities hedged at all times with short sales of stocks and/or stock index options. Where short sales are used, hedged assets may comprise an equal dollar value of long and short stock positions. Other variations use short sales unrelated to long holdings and/or puts on the S&P 500 index and put spreads. Conservative funds mitigate market risk by maintaining market exposure from zero to 100%. Aggressive funds may magnify market risk by exceeding 100% exposure and, in some instances, maintain a short exposure.

Equity Market Neutral: Exploit pricing inefficiencies between related equity securities, neutralizing exposure to market risk by combining long and short positions. One example is to build portfolios made up of long

	positions in the strongest companies in several industries and taking corresponding short positions in those showing signs of weakness.
Equity Market Neutral: Statistical Arbitrage	Utilize quantitative analysis of technical factors to exploit pricing inefficiencies between related equity securities, neutralizing exposure to market risk by combining long and short positions. Portfolios are typically structured to be market, industry, sector, and dollar neutral.
Equity Non-Hedge:	Commonly known as “stock-pickers,” funds that are predominantly long in equities; they do not always have a hedge in place, although they have the ability to hedge with short sales of stocks and/ or stock index options.
Event-Driven:	Also known as “corporate life cycle” investing, these funds invest in opportunities created by significant transactional events, such as spin-offs, mergers and acquisitions, bankruptcy reorganizations, recapitalizations, and share buybacks. The portfolio of some Event-Driven managers may shift in majority weighting between Risk Arbitrage and Distressed Securities, while others may take a broader scope.
Fixed Income: Arbitrage	Employ a variety of strategies involving investment in fixed income instruments, hedged to eliminate or reduce exposure to changes in the yield curve. The generic types of fixed income hedging trades include: yield-curve arbitrage, corporate versus Treasury yield spreads, municipal bond versus Treasury yield spreads, and cash versus futures.
Fixed Income: Convertible Bonds	Primarily long only convertible bonds.

Fixed Income: Diversified	Invest in a variety of fixed income strategies, including municipal bonds, corporate bonds, and global fixed income securities.
Fixed Income: High-Yield	Invest in mortgage-backed securities, including government agency, government-sponsored enterprise, private-label fixed- or adjustable-rate mortgage pass-through securities, fixed- or adjustable-rate collateralized mortgage obligations (CMOs), real estate mortgage investment conduits (REMICs), and stripped mortgage-backed securities (SMBSs). Funds may look to capitalize on security-specific mispricings.
Macro:	Take leveraged bets on anticipated price movements of stock markets, interest rates, foreign exchange, and physical commodities.
Market Timing:	Invest at the beginning of an uptrend in prices, and then switch out of these investments at the start of a downtrend in prices.
Merger Arbitrage:	Sometimes called Risk Arbitrage, involves investment in event-driven situations such as leveraged buy-outs, mergers, and hostile takeovers. These strategies generate returns by purchasing stock of the company being acquired, and in some instances, selling short the stock of the acquiring company.
Regulation D:	Invest in Regulation D securities, sometimes referred to as structured discount convertibles. The securities are privately offered to the investment manager by companies in need of timely financing.
Relative Value:	Attempt to take advantage of relative pricing

Arbitrage	discrepancies between instruments including equities, debt, options, and futures. Managers may use mathematical, fundamental, or technical analysis to determine misvaluations. Securities may be mispriced relative to the underlying security, related securities, groups of securities, or the overall market. Arbitrage strategies include dividend arbitrage, pairs trading, options arbitrage, and yield curve trading.
Short Selling:	Involves the sale of borrowed securities (not owned by the seller) in order take advantage of an anticipated price decline.
Fund of Funds:	Invest with multiple managers through a fund or a managed account. A Fund of Funds manager has discretion in choosing which strategies to invest in, and may allocate funds to numerous managers within a single strategy or to numerous managers in multiple strategies.
Managed Futures: (CTA) Index	The Barclay CTA Index represents the returns on a diversified portfolio of commodity futures managed by commodity trading advisors (CTAs). The return index is unweighted and rebalanced at the beginning of each year. In 2003 there were 359 CTA programs included in the index. To qualify for inclusion in the index an advisor must have four years of prior performance history, and new programs are not added to the index until after their second year.
Managed Futures: (BTOP 50) Index	The Barclay BTOP 50 Index represents the returns on the largest investable CTA programs, measured by assets under management.

1.3 Benefits of hedge funds

Many hedge fund strategies have the ability to generate positive returns in both rising and falling equity and bond markets. Academic research shows that hedge funds have higher returns and lower overall risk than traditional investment funds.

Inclusion of hedge funds in a balanced portfolio reduces overall portfolio risk and volatility and increases returns.

Huge variety of hedge fund investment styles-many uncorrelated with each other-provides investors with a wide choice of hedge fund strategies to meet their investment objectives.

Hedge funds provide an ideal long-term investment solution, eliminating the need to correctly time entry and exit from markets.

Hedge funds are expected to deliver absolute returns- they attempt to make profits under all circumstances, even when the relative indices are down. Absolute return is the return that an asset achieves over a certain period of time. This measure looks at the appreciation or depreciation (expressed as a percentage) that an asset-usually a stock or a mutual fund-achieves over a given period of time.

The incentive-based performance fees tend to attract the most talented investment managers to the hedge fund industry.

Hedge funds are often able to protect against declining markets by utilizing various hedging strategies. The strategies used of course vary tremendously depending on the investment style and type of hedge fund. But as a result of these hedging strategies, certain types of hedge funds are able to generate positive returns even in declining markets.

The future performance of many hedge fund strategies tends to be highly predictable and not dependent on the direction of the equity markets.

Diversification: investors can obtain a wider selection of risk and return profiles by combining hedge funds with traditional asset classes. The following illustrates the diversification benefit by incorporating a hedge fund allocation in various proportions with traditional asset classes.

Brooks and Kat (2002) examined the statistical properties of a number of freely available hedge fund index return series and they reached to the below conclusions.

- Many hedge fund index return distributions are not normal and exhibit negative skewness and positive excess kurtosis.
- The monthly returns of many hedge funds indices exhibit highly significant positive first-order autocorrelation.
- Several of monthly hedge fund index returns exhibit a high positive correlation with the stock market.
- There is correlation between different strategies.
- There is considerable heterogeneity between indices that aim to reflect the same type of strategy. As a result, investors' perceptions of hedge fund performance and value added will heavily depend on the indices studied.
- The available monthly return data underestimate true return volatility and thereby significantly overestimate the Sharpe ratio.
- Hedge fund indices offering skewness and kurtosis properties, so the Sharpe ratio will overstate the true performance.
- For the same reason there is unsuitability of mean-variance portfolio analysis, when hedge funds are involved.

CHAPTER TWO

BIASES

2.1 Introduction

There are many hedge fund databases that supply the researchers and managers with financial data. These databases hide some problems named biases, which have significant impacts on the performance measures. When the particular problem became perceivable, hedge fund databases conclude also defunct funds, which stop reporting for some reason like bankruptcy, liquidation, mergers, name, changes and sometimes voluntary stoppage of information reporting). In the following, we will study individually these biases.

2.1.1 Survivorship bias

Survivorship bias is the effect of considering only the performance of the funds that are alive and present in the database at the end of the sample period. So, many researchers conclude and the defunct funds in their sample to eliminate this bias. There are two definition of this bias. Firstly, it is the performance difference between surviving funds and dissolved funds. Secondly, it is the performance difference between living funds and all funds.

Ackermann, McEnally and Ravenscraft (1999) tested for differences in the mean and median absolute returns and Sharpe ratios of disappearing and extant funds. They weighted each fund's return by the number of months of the disappearing fund's return history. They moved on this process because they wanted to avoid performance outliers. Finally, they concluded that the survivorship bias is only 0.2%.

Capocci and Hubner (2004) used the two definitions of survivorship bias which we have referred above: the performance difference between surviving funds and dissolved funds and the performance difference between living funds and all funds. They reported this bias using both definitions for the whole period and for two subperiods 1984–1993 and 1994–2000. They calculated a monthly survivorship bias of 0.36% (or 4.45% per annum) for the whole period. A look at a subperiod biases indicated that survivorship bias is much higher after 1994.

Edwards and Caglayan (2001) included the return histories for 496 no surviving hedge funds from the MAR database and they estimated the alphas (excess returns) for those funds and all surviving funds. They also estimated that if the returns of the nonsurviving hedge funds had not been included in the analysis, there would have been a survivorship bias of 1.85% in average annual hedge fund returns. Finally, this bias ranged from a low of 0.36% for market-neutral funds to a high of 3.06% for long-only funds. Specifically, they found a survivorship bias of 1.85% in average annual hedge fund returns.

Barry (2003) found a survivorship bias of 3.8% in average annual hedge fund returns.

Ibbotson and Chen (2006) calculated the after-fee monthly return data for each fund. With the live, dead and backfill funds, which they have calculated, they constructed the following six subsamples of the returns data in order to create an unbiased return sample:

- Live funds only with backfill data.
- Live funds only without backfill data.
- Live and dead funds with backfill data.
- Live and dead funds without backfill data.
- Dead funds only with backfill data.
- Dead funds only without backfill data.

For each subsample, they compiled three portfolios and calculated the monthly returns for each:

- An equally-weighted portfolio.
- A value-weighted (using previous month's assets under management) portfolio.
- An equally-weighted portfolio with only funds that have reported an asset under management (AUM) amount.

In the following, they analyzed the survivorship bias in hedge fund return data by comparing returns on the above three portfolios across the six subsamples of funds. Specifically, for survivorship bias, they compared the returns between portfolios with and without the dead funds. In the database with backfilled return data, the equally weighted portfolio with live only funds returned 16.45% per year, compared to 13.62% with both live and dead funds. Therefore, with backfilled data the survivorship bias is estimated to be 2.74% (16.45%–13.62%) per year. But including backfilled return data underestimated the potential survivorship bias in the data. When they excluded the backfilled data, the live only funds returned 14.74% per year, compared to 9.06% for the equally weighted portfolio with dead and live funds. This indicated a more accurate estimate of survivorship bias of 5.68% (14.73%–9.06%) per year, which was substantially higher than others have estimated.

Malkiel and Saha (2005) calculated the survivorship bias. They distinguished funds in live and defunct. They calculated the difference in means and medians using the t-test. They found that survivorship bias exists.

2.1.2 Instant history bias or backfill bias

Backfill bias is the consequence of adding a hedge fund whose earlier good returns are backfilled between the inception date of the fund and the date it enters the database, while bad track records are not backfilled. The most known calculation method of this bias is the evaluation of the difference between the return of an adjusted observable portfolio, the returns corresponding to the incubation period are dropped, and the return of a non-adjusted observable portfolio. If this difference between these portfolios is not significant then the backfill bias is not a serious problem for the performance measure.

Ackermann, McEnally and Ravenscraft (1999) followed this method. Their non-adjusted observable portfolio was the elimination of the first two years of reported data. They took raw returns and Sharpe ratio statistics and they found that the difference was not statistically significant.

Capocci and Hubner (2004) estimated instant history bias in two steps. On the one hand, they estimated the average monthly return using the portfolio that invests in all funds from their database each month (we called this portfolio the observable one). On the other, they estimated the average monthly return from investing in all these funds after deleting the first 12, 24, 36 and 60 months of returns (we called this portfolio the adjusted observable one). For the 1/1984–6/2000 period, the observable monthly return averaged 1.49%, while the adjusted observable one was 1.42% (when deleting the 12 first months), 1.26% (24 months), 1.20% (36 months), and 1.15% (36 months).

Edwards and Caglayan (2001) in their study, excluded the first 12 month of their data to proceed following, because they found that the average annual return for hedge funds during their first year of their existence is about 1.17 percentage points higher than their average returns in subsequent years.

Fung and Hsieh (2000) estimated backfill bias as 1.4% for average annual hedge fund returns.

Ibbotson and Chen (2006) followed the process which we have described in the previous paragraph. In order to calculate the backfill bias, they compared the returns between the subsamples with and without the backfilled return data. Furthermore, they analyzed the backfill bias in hedge fund return data by comparing returns on the above three portfolios across the six subsamples of funds.

In the database with backfilled return data, the equally weighted portfolio with live only funds returned 16.45% per year, compared to 13.62% without the backfilled data. Therefore, the survivorship bias is estimated to be 2.83% (16.45%–13.62%) per year for the live funds. When they included the dead fund data, the equally weighted portfolio with backfilled data returned 13.62% per year, compared to 8.98% for the equally weighted portfolio over without the backfilled data. This indicated that backfill bias is 5.01% per year over the live plus dead sample. Thus the backfill bias can be substantial, especially when using the complete sample of live plus dead funds.

They also found that the backfill bias was measured to be much smaller using the value-weighted portfolios than the equally weighted portfolios. The average returns was calculated using both the equally weighted portfolio and the value-weighted portfolio, constructed with only funds that have reported their assets under management. For the equally weighted portfolio with AUM, the backfill bias is estimated to be 4.64% (13.62%–8.98%). For the value-weighted portfolio, the backfill bias is estimated to be only 0.27% (11.93%–

11.66%). This seems to indicate that bigger funds are much less likely to have backfilled data in the database.

Malkiel and Saha (2005) calculated the backfill bias. They compared the yearly returns of the backfilled and contemporaneously reported returns and they applied Chi-squared test of the differences between the two groups. Applying tests between the means and between the medians, they found that the differences between backfilled and not backfilled returns were highly significant.

Alexander and Dimitriu (2004) computed for each fund the difference between the monthly average of the excess return (over S&P 500) in the first year and the monthly average of the excess return in the first five years. The mean of the difference was 0.33% equivalent to an annual difference of 3.97%. The distribution of differences was positively skewed, suggesting that existence of a small number of funds having much higher returns in the first year than in the rest of the reporting period. In order to isolate the instant history bias they used dummy variables for the first year of reporting in all factor models.

2.1.3 Selection bias

This kind of bias will be created only if hedge funds with good performance choose to report their performance. In this case, the reported data may overstate true hedge fund performance. On the other hand, this bias is limited, when very successful hedge funds do not disclose their performance, because they have reached their goal in terms of assets under management. It is important to refer that if we want to calculate this bias, then we need the data from the funds that they do not disclose their performance, something that is impossible. Edwards, Caglayan (2001) and Fung and Hsieh (2000) believe that selection bias is probably negligible and it is not affect the performance measures. Fung and Hsieh (2000) calculate this bias of 1.4% and Park, Brown and Goetzmann (1999) of 1.9%.

2.1.4 Multi-period sampling bias

This kind of bias may exist if some hedge funds have very short return histories.

Edwards and Caglayan (2001) required that all hedge funds in the sample have a minimum of 24 months of returns, after excluding the first 12 months of returns for all hedge funds for any potential instant history bias. After this effort, they estimated a 24-month-minimum history was imposed (after the first 12 months of returns were excluded), the average annual hedge fund return is 0.32% higher than when no minimum history requirement is imposed on the sample of funds. It was notable that the difference in return is nearly the same (0.29%).

Alexander and Dimitriu (2004) estimated multi-period sampling bias and they found it negative but negligible.

CHAPTER THREE

PORTFOLIO'S THEORY- RISK MEASURES

3.1 Introduction

This chapter concludes the portfolio's theory of Markowitz (1952), some measures that are used in order to test the operation of our portfolios and risk measures, classic and newer approaches, which offered us the suitable tools to determine the risk-return trade-off.

3.2 Portfolio's theory

The classical portfolio theory of Markowitz (1952) underlies the foundations of modern finance and many of today's practitioner models. Assuming investors have quadratic preferences; its application requires knowledge of the first two moments of the returns distribution. For this reason, the analysis of the portfolio's theory is depended on the mean-variance criterion. This means that we discuss for the mean return of a financial asset and its variance. As we say until now, the mean return is something positive for investor in contrast to the variance.

In our study, we have two financial assets A and B. r_A and r_B are the mean return of financial assets A and B, respectively. In the same way, we denote σ_A and σ_B their standard deviations. We also denote $\sigma_{A,B}$ the covariance of the returns of A and B. So, we can take the correlation from the following type: $p_{A,B} = \sigma_{A,B}/\sigma_A\sigma_B$.

In the following, we have a portfolio P, which comprises these assets. We have w_A the percentage of participation from the first asset and w_B from the second one. Finally, we can conclude that $w_A + w_B = 1$.

The mean return of the portfolio P is $r_P = w_A r_A + w_B r_B$. The second step is to define the variance of the portfolio P, which is given by,

$\sigma_P^2 = \text{var}(w_A r_A + w_B r_B) = w_A^2\sigma_A^2 + w_B^2\sigma_B^2 + 2w_A w_B \sigma_{A,B}$, where $\sigma_{A,B} = \sigma_A\sigma_B\rho_{A,B}$, consequently, we take the following expression: $\sigma_P^2 = w_A^2\sigma_A^2 + w_B^2\sigma_B^2 + 2w_A w_B \sigma_A\sigma_B p_{A,B}$, where $-1 \leq p_{A,B} \leq 1$.

We can distinguish four conclusions that arise in regard to $p_{A,B}$'s value.

1) If $p_{A,B} = 1$, then there is perfect positive correlation between mean returns of A and B. In this case, there is no impact in the risk of the portfolio P. $\sigma_P = w_A\sigma_A + w_B\sigma_B$
2) If $p_{A,B} = 0$, then there is less risk of portfolio P. This means that investors have profits. $\sigma_P = \sqrt{w_A^2\sigma_A^2 + w_B^2\sigma_B^2}$
3) If $p_{A,B} = -1$, then there is perfect negative correlation between mean returns of A and B, which means that if we suitably choose the proportion of the weights w_A and w_B, then we can construct a portfolio with zero risk. $\sigma_P = \sqrt{w_A^2\sigma_A^2 - w_B^2\sigma_B^2}$

3.3 Comparison of portfolios

As we saw, the construction of a portfolio was the first step. The second is its performance. We can evaluate it in comparison with other portfolios, which are constructed under the same constraints or by using a benchmark. So we exhibit some techniques that can measure the operation of portfolios.

- Cumulative return

The return of T periods is given by $r_t(T) = r_t + r_{t-1} + \ldots + r_{t-T+1}$.

- Mean return

The mean return of T periods is given by $\bar{r} = \sum_{t=1}^{T} r_t / T$.

- Annualized return

The annualized return is gathered by the multiplication of mean return with 12 (months) or 252 (trading days). Specifically, $r_{an} = \bar{r} \times 12$.

- Geometric mean of returns

Firstly, we need the logarithm of geometric mean which is given by $\bar{r}_{log} = \sum_{t=1}^{T} \log(1 + r_t) / T$. Finally, the geometric mean of returns is given by the following expression: $\bar{r}_{geom} = e^{\bar{r}_{log}} - 1$.

- Success rate

This rate gives us the percentage for which the returns of a portfolio are bigger from the returns of a benchmark for T periods. It is given by $SR = \frac{1}{T} \sum_{t=1}^{T} I_t$, where $I_t = \begin{cases} 0 \text{ if } r_t \leq r_{b,t} \\ 1 \text{ otherwise} \end{cases}$ is the index of success, $r_{b,t}$ is the return of the benchmark in t.

- Information ratio

The information ratio for T periods is given by the following expression: $IR = \sum_{t=1}^{T} r_{dif,t} / \mathrm{stdev}(r_{dif,t})$, where $r_{dif,t} = r_t - r_{b,t}$ is the difference between the returns of portfolio P and the returns of the benchmark.

3.4 Risk measures

Furthermore, we need risk measures to test the capability of a portfolio P. We can use two alternative types of risk, the total risk, which we showed below how to calculate it, and the systematic or non-diversifiable risk, which is measured by the parameter beta (risk premium). Afterwards, we will show some risk measures.

3.4.1 Classic performance measurements

- Sharpe ratio

Sharpe ratio is an absolute risk-adjusted performance measure, which was developed by Sharpe (1996), with the following expression: $S_p = \left(E\left(R_p\right) - R_f\right) / \sigma\left(R_p\right)$, where $E\left(R_p\right)$ is the expected return of the portfolio, R_f is the risk-free rate and $\sigma\left(R_p\right)$ is the standard deviation of the portfolio returns.

- Traynor ratio

Traynor ratio, was developed by Traynor (1965), is the same type of performance measure as Sharpe ratio, which is given by $T_p = \left(E\left(R_p\right) - R_f\right) / \beta_p$, where $E\left(R_p\right)$ is the expected return of the portfolio, R_f is the risk-free rate and β_p is the beta of the portfolio.

- Jensen's alpha

Jensen's alpha, which was developed by Jensen (1968), is a relative risk-adjusted performance measure, which is given by $R_{p_t} - R_{f_t} = a_p + \beta_p\left(R_{M_t} - R_{f_t}\right) + \varepsilon_{p_t}$, where R_{p_t} is the return of the portfolio, R_{f_t} is the risk-free rate, β_p is the beta of the portfolio and R_{M_t} is the market return.

3.4.2 Newer approaches to performance measurements

- Lower partial moments

Lower partial moments measure risk by negative deviations of the returns realized in relation to a minimal acceptable return τ. The LPM of order n for asset i is calculated as by the below formula: $LPM_{ni}(\tau) = (1/T)\sum_{t=1}^{T} \max[\tau - r_{it}, 0]^{n}$. The choice of order n determines the extent to which the deviation from the minimal acceptable return is weighted. The LPM of order 0 can be interpreted as shortfall probability, LPM of order 1 as expected shortfall and LPM of order 2 for $\tau = r_i^d$ as semi-variance. Three specific measures related with LPM. Omega is one of these and has the following formula: $\text{Omega}_i = \left(r_i^d - \tau / LPM_{1i}(\tau)\right) + 1$. Sortino ratio has the following form: $\text{Sortino ratio}_i = \left(r_i^d - \tau\right) / \sqrt[2]{LPM_{2i}(\tau)}$ and finally Kappa3: $\text{Kappa3}_i = \left(r_i^d - \tau\right) / \sqrt[3]{LPM_{3i}(\tau)}$. These measures compute the excess return as the difference between the average return and the minimal acceptable return.

There are the higher partial moments (HPM), which in contrast to LPM that measures only negative deviations of returns from a minimal acceptable return τ, measures positive deviations. So, we have the upside potential ratio which combines the HPM order 1 with the LPM of order 2. $\text{Upside potential ratio}_i = HPM_{1i}(\tau) / \sqrt[2]{LPM_{2i}(\tau)}$.

- Measures on the basis of drawdown

We also have measures on the basis of drawdown. The drawdown of an asset i, is the loss incurred over a certain investment period. $r_{i,t-T}$ denotes the return of an asset i, realized over the period from t to T. MD_{i1} denotes the lowest return of an asset i and MD_{i2} the second lowest return and so on. The smallest return MD_{i1} is negative and denotes the maximum possible loss that could have been realized in the considered period of time. Three measures use drawdown. Specifically, use the maximum drawdown, an average above the N largest drawdows and a type of variance above the N largest drawndowns as risk measures. These measures are the following:
$\text{Calmar ratio}_i = \left(r_i^d - r_f\right) / \left(-MD_{i1}\right)$, $\text{Sterling ratio}_i = \left(r_i^d - r_f\right) / (1/N)\sum_{j=1}^{N}\left(-MD_{ij}\right)$,
$\text{Burke ratio}_i = \left(r_i^d - r_f\right) / \sqrt[2]{\sum_{j=1}^{N} MD_{ij}^2}$.

- Value at Risk

There are measures on the basis of value at risk. It describes the possible loss of an investment which is not exceeded with a given probability of 1-a in a certain period. In case of normality of the returns, the standard value-at-risk has the following formula: $\mathrm{VaR}_i = -\left(r_i^d + z_a\sigma_i\right)$, where z_a denotes the a-quantile of the standard normal distribution. The Value-at-Risk has parametric and non-parametric approaches. Nonparametric VaR does not impose any parametric assumption on the distribution of a portfolio's returns. It is based on the left tail of the actual empirical distribution.

The Cornish-Fisher (1937) expansion is one of the parametric approaches to estimating VaR. The traditional parametric method assumes that the returns are normally distributed. This means that the VaR measure depends only on the mean and the standard deviation of returns. Under this assumption, the 95% VaR based on normality is calculated by the following formula: $\mathrm{VaR\_Normal}(a = 0.05) = -\left(\mu + z(a) \times \sigma\right) = -\left(\mu - 1.645 \times \sigma\right)$, where μ and σ are, respectively, the sample mean and standard deviation of returns, $1 - \alpha$ is the confidence level and $z(a)$ is the critical value from the standard normal distribution corresponding to the confidence level. But, usually, the returns do not based on normality. To deal with non-normality in the return distribution, we use the Cornish-Fisher expansion. Consequently, the parametric VaR is approximated by the Cornish-Fisher expansion (VaR_CF) in order to incorporate in the equation the skewness and kurtosis of the empirical distribution. The following equation shows the first four terms of the Cornish-Fisher expansion for the α percentile of $(R - \mu)/\sigma$,

$\Omega(a) = z(a) + \frac{1}{6}\left(z(a)^2 - 1\right)S + \frac{1}{24}\left(z(a)^3 - 3z(a)\right)K - \frac{1}{36}\left(2z(a)^3 - 5z(a)\right)S^2$ and the other equation shows the parametric VaR, $\mathrm{VaR\_CF}(a) = -\left(\mu + \Omega(a) \times \sigma\right)$, where μ is the average return, σ is the standard deviation, S is the skewness, and K is the excess kurtosis of the monthly returns, $1 - \alpha$ is the confidence level and $z(\alpha)$ is the critical value from the standard normal distribution. Note that if the portfolio return is normally distributed, skewness (S) and excess kurtosis (K) are set equal to zero, which makes $\Omega(a)$ equal $z(\alpha)$ and thus, VaR_ CF(α) equals VaR_ Normal(α).

- Semi-deviation (SEM)

Another risk measure is the semi-deviation (SEM). In this case we consider the deviation from the mean only when it is negative. It is given by the following formula: $\text{Semi-deviation}(SEM) = \sqrt{E\left\{\text{Min}\left[(R-\mu),0\right]^2\right\}}$, where μ is the average return.

- Expected Shortfall (ES)

Another measure is the Expected Shortfall. This measure calculates the information on how big could be the loss. Specifically, it is the quantity which value at risk can not calculate. ES can be expressed as follow:

$$ES_t(a,\tau) = -E\left[R_{t+T} \mid R_{t+T} \le -VaR_t(a,\tau)\right] = \frac{\int_{v=-\infty}^{-VaR_t(a,t)} v f_{Rt}(v)dv}{F_{R,t}\left[-VaR_t(a,\tau)\right]} = \frac{\int_{v=-\infty}^{-VaR_t(a,t)} v f_{Rt}(v)dv}{a}$$

where R_{t+T} denotes the portfolio return during the period between t and t+τα, f_{Rt} denotes the conditional probability density function (PDF) of R_{t+T}, $F_{R,t}$ denotes the conditional cumulative distribution function (CDF) of R_{t+T} conditional on the information available at time t and $F_{R,t}^{-1}$ denotes the inverse function of $F_{R,t}$ and 1-a is the confidence interval.

ES distinguished in parametric and non-parametric approaches. Non-parametric expected shortfall used the left tail of the actual empirical distribution using individual hedge funds. For example, we suppose a fund A with n observations. We estimate the 0.05 percentile of the return distribution using n return values and set it to the 95% VaR_NP. In the following, we sort all the return values less or equal to the 95% VaR_NP and take the average of them as the 95% ES_NP. In the case of the parametric method, Expected shortfall is based on the Cornish-Fisher Expansion; we estimate the 95%

Cornish-Fisher VaR_CF, we take the returns less than or equal to the 95% VaR_CF, we calculate the average of these and we use the average as the 95% ES_CF of the fund.

- Tail Risk (TR)

Another measure is the tail risk (TR), which measures the deviation of losses larger than VaR from mean. TR is defined as follows: $TR_t(a,\tau) = \sqrt{E_t\left\{\left(R_{t+T} - E_t\left(R_{t+T}\right)\right)^2 \mid R_{t+T} \leq -VaR_t(a,\tau)\right\}}$. TR captures in more precisely way, the impact of an extremely low return observation because the deviations from mean are squared before being averaged. TR_NP denotes tail risk based on non-parametric (VaR_NP) and (TR_CF) denotes tail risk based on (VaR_CF).

3.5 Application on the risk measures

Liang and Park (2007) used alternative measures such as semi-deviation, VaR, expected shortfall (ES) and tail risk (TR) and compared them with standard deviation, in terms of their explanatory power of the cross-sectional variation in expected returns of hedge funds. Initially, they sorted individual hedge funds by a risk measure at the end of each period and form decile portfolios. Then, they compared the rate of return on the most risky portfolio with that from the least risky one during the following period. They used the empirical distribution of this return differential to test the presence and significance of the relationship between risk and expected return. Afterwards, they tested the risk-return trade-off at the individual fund level, using time series data to estimate risk for each fund. In the following, they used the estimate in a cross-sectional regression at each period.

They confirmed that skewness and kurtosis should not be ignored when we analyze the risk of hedge funds. Specifically, they provided evidence that the cross-sectional variation in expected returns of hedge funds can be explained better when we take higher moments into consideration. They showed that expected shortfall (ES) is superior to VaR, as a risk measure of hedge funds. They, also, concluded that the Cornish-Fisher expansion is better than the non-parametric method when we estimate downside risk measures.

Eling and Schuhmacher (2007) compared the Sharpe ratio with some performance measures. Specifically, they compared the Sharpe ratio with measures that are based on lower partial moments (LPM) such as Omega, Sortino ratio and Kappa3. Measures, which are depended on the basis of drawdown as Calmar ratio, Sterling ratio and Burke ratio. Measures, which depends on Value-at-Risk such as Excess-return-on-VaR $= \left(r_i^d - r_f\right)/VaR_i$, Conditional-Sharpe-ratio $= \left(r_i^d - r_f\right)/CVaR_i$ and finally, Modified-Sharpe - ratio $= \left(r_i^d - r_f\right)/MVaR_i$. Traynor ratio and Jensen's alpha are the last two measures, which the researchers used in their comparisons.

They concluded that even though hedge fund returns are not normally distributed, the first two moments (mean and variance) describe the return distribution sufficiently well. They presented as possible explanation that hedge fund returns are elliptically distributed. The mean-variance analysis can be used for elliptical distributions, and not only for multivariate normal distributions. Their study showed that the choice of performance measure does not have a crucial influence on the relative evaluation of hedge funds. Specifically, the Sharpe ratio can be used both when the hedge fund represents the entire risky investment and when it represents only a portion of the investor's risky investment.

Gregoriou and Gueyie (2003) proposed a modified Sharpe ratio as an alternative measurement for hedge funds returns. The difference is that the denominator is a modified Value-at-Risk instead of normal standard deviation. The standard Value-at-Risk considers mean and standard deviation while the modified approach considers not only the first two moments but skewness and excess kurtosis. They tested the modified measurement on 90 live funds of hedge funds in the Zurich capital market from 1997 to 2001 and they concluded that large hedge funds are better in controlling risk-adjusted performance compared to small funds. They suggested that this finding might be explained by the liquidity of large hedge funds.

CHAPTER FOUR

METHODOLOGIES

4.1 Introduction

The Capital Asset Pricing Model (CAPM) is a single factor model, which implies that security prices are governed by their market risks and not their firm-specific risks. Specifically, it is a statistical regression model with the following expression: $R_{it} = a_i + \beta_i R_{mt} + \varepsilon_{it}$, where R_{it} is the return on a given portfolio (or fund) i, a_i is the abnormal performance of the portfolio (or fund) i, β_i is the sensitivity of the portfolio (or fund) i and R_{mt} is the market return at time t.

Another class of models with high degree of popularity are the multifactor models. There are three types of multi factor models. First, it is the implicit factor model, second, the explicit macro-factor model and finally the explicit micro-factor model. The general type is $R_{it} = a_i + \sum_{k=1}^{K} \beta_{ik} F_{kt} + \varepsilon_{it}$, where R_{it} is the return on a given portfolio (or fund) i at time t, a_i is the abnormal performance of the portfolio (or fund) i, β_{ik} the sensitivity of the portfolio (or fund) i for k factor and F_{kt} is the return on factor k at time t.

The implicit factors are obtained through Principal Component Analysis. The aim is to explain the return series of observed variables through a smaller group of non-observed implicit variables. Explicit macro-factor model is an approach, which use macroeconomic variables as factors. The sensitivity of the factors is estimated via regressions. In this type of model, we must carefully choose these factors because we can conclude to model misspecification. Stepwise regression is a good technique for the discrimination of factors. In the case of explicit micro-factor models, the selected factors depend on the specific features of the funds.

Another approach is the application of the conditional models. Static asset pricing models imply that risk and performance are constant over time.

On the other hand investment decisions are based on public information and dynamic trading strategies.

In the following paragraphs, we will see all these models with many diversifications in regard to hedge fund indexes, market indexes and fund's characteristics.

4.2 Asset class factor models

Liang (1999) used an asset class factor model to evaluate performance and analyze styles for hedge funds. Its formula is given by the following: $R_t = a + \sum_{k} \beta_k F_{kt} + \varepsilon_t$. Specifically, he used the following asset classes: S&P 500 index, MSCI world equity index, MSCI emerging market index for equity markets, Salomon brothers world government bond index, Salomon brothers government and corporate bond index for bond markets, Federal Reserve Bank trade-weighted dollar index for currency, Gold price for commodities, One-month Eurodollar deposit for cash.

Furthermore, he used 16 different hedge fund categories which they obtained by the HFR database and were the following: Composite, convertible arbitrage, distressed securities, emerging markets, fixed income, foreign exchange, growth, macro, market neutral, market timing, merger arbitrage, opportunistic, sector, short-selling, value and funds of funds. He used stepwise regression to select variables according to the standard AIC criterion. He concluded that hedge funds follow dynamic trading strategies rather than buy-and-hold strategies. He also found that hedge funds have low systematic risk. Finally, he concluded that hedge funds have higher Sharpe ratios, lower market risks and higher abnormal returns.

Ackermann, Mc Enally, Ravenscraft (1999) used a single-factor model with two common equity indices (S&P 500 and MSCI EAFE total return indices), seven MAR hedge fund investment styles (event driven, funds of funds, global, global macro, market neutral, short sales, US opportunistic) and four sample periods (hedge funds that have at least two, four, six or eight consecutive years of performance). It is significant to refer that they gave more emphasis to Sharpe ratios with known disadvantages. They found that annualized Jensen alphas were significantly positive for hedge funds and ranged from 6% to 8% per year for different time periods, except for the period 1994-95. They did not estimate annualized alphas for alternative investment styles of hedge funds.

Furthermore, they calculated the differences between hedge funds and some market indices (S&P 500, MSCI EAFE, MSCI World, Wilshire 5000, Rushell 2000, Balanced- 60% S&P500 and 40% Lehman Aggregate Bond, Lehman Aggregate Bond, Lehman Government/Corporation Bond). They calculated the mean and median Sharpe ratio for the hedge funds in each of four sample periods and for each time period. They applied a test of difference between the index Sharpe ratio and the mean or median hedge fund sample value. Finally, they concluded that hedge fund did not beat the market but appeared to earn enough of superior return to cover their costs.

Capocci and Hubner (2004) applied four different asset pricing models to determine whether or not hedge funds as a whole and depending on the strategy followed have outperformed the market. For all models, they have applied Newey-West (1987) test for standard errors to adjust for any autocorrelation in the returns. They used event driven, global, global macro, market neutral, short-sellers, US opportunistic, long-only leveraged, market timing, equity non-hedge, foreign exchange, sectors and FOFs.

They started their application with the CAPM model, $R_{Pt} - R_{Ft} = a_P + \beta_P (R_{Mt} - R_{Ft}) + \varepsilon_{Pt}$, where, R_{Pt} is the return of the fund P on month t, R_{Ft} is the risk-free return on month t, R_{Mt} is the return on the market portfolio on month t, ε_{Pt} is the error term, a_P and β_P are the intercept and the slope coefficient of the regression, respectively.

They concluded that this model gave betas that were rather low, which means that they needed a more detailed model. More than 80% of the individual funds did not significantly outperform the market.

In the following, they applied the three-factor model of Fama and French (1993) and its international version of Fama and French (1998). They took account the size and the book-to-market ratio of the firms. $R_{Pt} - R_{Ft} = a_P + \beta_{P1} (R_{Mt} - R_{Ft}) + \beta_{P2} SMB_t + \beta_{P3} HML_t + \beta_{P4} IHML_t + \varepsilon_{Pt}$, where,

SMB_t: The factor mimicking portfolio for size (small minus big), HML_t is the factor mimicking portfolio for book-to-market equity (high minus low), $IHML_t$ is the international factor mimicking for book-to-market equity.

They also applied the four-factor model of Carhart (1997). This model takes into account size, book-to-market ratio and a factor for the momentum effect which is defined as buying stocks that were past winners and selling past losers. In above, we present the four-factor model of Carhart (1997).

$$R_{Pt} - R_{Ft} = a_P + \beta_{P1}(R_{Mt} - R_{Ft}) + \beta_{P2}SMB_t + \beta_{P3}HML_t + \beta_{P4}PR1YR_t + \varepsilon_{Pt},$$

where, $PR1YR_t$ is the factor-mimicking portfolio for the momentum effect.

Finally, they applied an extended multi-factor model:

$$\begin{aligned} R_{Pt} - R_{Ft} = a_P &+ \beta_{P1}(R_{Mt} - R_{Ft}) + \beta_{P2}SMB_t + \beta_{P3}HML_t + \beta_{P4}IHML_t + +\beta_{P5}PR1YR_t \\ &+ \beta_{P6}(MSWXUS_t - R_{Ft}) + \beta_{P7}(LAUSBI_t - R_{Ft}) + +\beta_{P8}(SWGBI_t - R_{Ft}) \\ &+ \beta_{P9}(JPMEMBI_t - R_{Ft}) + \beta_{P10}(LEHBAA_t - R_{Ft}) + +\beta_{P11}(GSCI_t - R_{Ft}) \\ &+ \varepsilon_{Pt} \end{aligned}$$

where, $LEHBAA$ is the default factor (Lehman BAA Corporate Bond Index) as introduced by Agarwal and Naik (2002), R_{Mt} is the return on the Russell 3000 index, $MSWXUS$ is the return of the MSCI World Index excluding US, $LAUSBI$ is the return on the Lehman Aggregate US Bond Index, $GSCI$ is the return of the Goldman Sachs Commodity Index, $SWGBI$ is the return on the Salomon World Government Bond Index, $JPMEMBI$ is the return of the JP Morgan Emerging Market Bond Index and $LEHBAA$ is the return of the Lehman BAA Corporate Bond Index.

Edwards and Caglayan (2001) applied a six-factor Jensen alpha for individual hedge funds employing eight different investment styles. So, the applicative multi-factor model is the following:

$$\begin{aligned} R_i - R_f = a + \beta(S\&P500 - R_f) + s(SMB) + h(HML) + w(WML) + g(TERM) \\ + k(DEF) + \varepsilon_i \end{aligned},$$

where, R_i is the monthly return of hedge fund i, R_f is the 30-day Treasury bill rate, HML is the monthly return on a portfolio of high book-to-market stocks minus the monthly return on a portfolio of low book-to-market stocks, SMB is the monthly return on a portfolio of small stocks minus the monthly return on a portfolio of large stocks, WML is the monthly return on a stock portfolio of the past year's winners minus the monthly return on stock portfolio of the past year's losers, TERM is the monthly return on a stock portfolio of the past year's winners minus the 1-month-lagged 30-day T-bill return, DEF is the monthly return on long-term corporate bonds minus the monthly return on a portfolio of long-term government bonds.

They concluded that on average hedge funds earned significantly positive excess returns and that these returns differed markedly by investment style.

Do, Faff and Wickramanayake (2005) started with the application of the Fama and French three-factor model. They developed a multifactor model as an extension of the Fama and French model. Their model is the below:

$$XR_{it} = a_i + \beta_{i1}XR_{mt} + \beta_{i2}SMB_t + \beta_{i3}HML_t + \beta_{i4}XCBI_t + \beta_{i5}XEMI_t + \beta_{i6}XGBI_t + \beta_{i7}XCI_t + \beta_{i8}XWI_t + \varepsilon_{it},$$

where, XCBI is the return on on Lehman corporate bond index, XEMI is the excess return on Lehman emerging market index, XGBI is the excess return on JP Morgan global government bond index, XCI is the excess return on GSCI Commodity index, and XWI is the excess return on MSCI world index excluding Australia.

When they used the traditional Fama and French model, they concluded that the average adjusted R-squared was rather low, 0.309. They also found that 80% of the funds have positive market alpha with almost 40% of these being significant at the 5% level. SMB and HML seem to have significant influence on the model. When they used the extended model found that the average adjusted R-squared is 0.43. Only 16% of the funds have significant SMB and HML at 5% level. The rest of the macroeconomic factors had a significant contribution in the model for 10-15% of cases. So, there are no dominant factors for Australian hedge fund managers.

They also tested the Australian hedge fund managers if they had significant market timing ability. They used the model which was applied by Fung et.al (2002) and had the following expression: $XR_{it} = a_i + \beta_{i1}XR_{mt} + \beta_{i2}(XR_{mt}D_t) + \varepsilon_{it}$, where, D is a dummy variable which takes the value of -1 for a bear month and zero otherwise. A bear (bull) month is deemed to be a month when the market index has a return lower (higher) than -1% (+1%). For the market timing ability model, they concluded that the two timing betas were not significant, consequently Australian hedge fund managers tend to have superior relative performance by means of security selection but not from market timing.

Ding and Shawky (2007) modeled returns for hedge funds by asset class. Firstly, they applied a model with hedge fund returns and higher moments. Specifically, they regressed the mean monthly returns X_i, onto the cross-sectional mean, standard deviation, skewness and kurtosis: $X_i = a + \beta_0\sigma_i + \beta_1 S_i + \beta_2 k_i$. They found that for the live funds, in every category both the standard deviation and the skewness coefficients are positive and highly significant at the 1% level. For the dead funds, all but the Fixed Income category also showed significant skewness. The coefficients for kurtosis for both live and dead funds did not exhibit significant results. In conclusion, investment strategies that produce positive skewness contribute significantly to hedge fund returns.

Secondly, they used a two-factor (two-index) model with the following form: $R_t - R_t^{T-Bill} = a + \beta_1\left(R_t^{S\&P500} - R_t^{T-Bill}\right) + \beta_2\left(R_t^{VBMFX} - R_t^{T-Bill}\right) + \varepsilon_t$, where R_t is the value-weighted return of hedge funds invested in an asset class in month t.

They used S&P 500 index to proxy for the stock market, the Vanguard Total Bond Market Index Fund to proxy for the overall bond market performance and 13-week T-Bill rate to proxy for risk free rate. They concluded that equity funds as global funds loaded significantly on the S&P500 index, the fixed income and Futures categories loaded significantly on the Vanguard Bond Index Fund and the only hedge fund category that loads significantly on both equity and fixed income indices is FOF.

Third, they used Sharpe ratio, Information ratio and Jensen's alpha for each hedge fund category and of each of the three market indexes, which we will refer below. They found that the result shown for live funds, all hedge fund categories seem to achieve above average performance when compared to the three market indices.

In the second part of the study, they focused on estimating the performance of equity hedge funds using four alternative models. They began with the single index model. Specifically, they used the Wilshire 5000 index to proxy for the market portfolio with the following formulation: $R_t - R_t^{T-Bill} = a + \beta_1\left(R_t^{Will5000} - R_t^{T-Bill}\right) + \varepsilon_t$. They found that the estimated alpha for all three categories was positive and statistically significant at the 1% level for both live and dead funds. The beta coefficient was also highly significant for all three categories.

In the following, they applied a model with this specific formulation,

$$R_t - R_t^{T-Bill} = a + \beta_1\left(R_t^{S\&P500} - R_t^{T-Bill}\right) + \beta_2\left(R_{t-1}^{S\&P500} - R_{t-1}^{T-Bill}\right) + \beta_3\left(R_{t-2}^{S\&P500} - R_{t-2}^{T-Bill}\right)$$
$$+ \beta_4\left(VOL_t^{S\&P500} - VOL_t^{S\&P500}\right) + \varepsilon_t$$

where they incorporated the contemporaneous S&P 500 index returns and the one-month and two-month lagged index returns. They followed this method because they wanted to know if all publicly available information reflects to a contemporaneous market index. If it happens, then it is possible to have persistence. Finally, they concluded that live hedge funds still generate significantly positive alphas.

They also applied the Fama and French factor (SMB and HML) against the Wilshire 5000 index. They concluded that live hedge funds still generate significantly positive alphas.

Finally, they applied Harvey-Siddique model adjusting for skewness. This model assumes that the stochastic discount factor is quadratic in the market return, which implies an asset pricing model where the expected excess return is determined by its conditional covariance with the market return and the square of market return which represents conditional coskewness. This model is similar to Traynor-Mazuy model to test for market timing ability, which has market timing ability if the coefficient on the square term is significant positive. The specified model which they applied was the following: $R_{i,t} = a_i + \beta_i R_{M,t} + c_i R_{M,t}^2 + \varepsilon_{i,t}$, where β_i is the systematic risk of asset i, c_i represents the coskewness of asset i relative to the market. From the application of this model gathered that all of the intercept terms were statistically significant at the 1% level for both live and dead funds. The skewness term was statistically significant for the equity hedge strategies but not for FOF category.

Brown, Goetzmann, Ibbotson (1999) applied a single factor model using as a benchmark the S&P 500 index. Specifically, they calculated the arithmetic and geometric mean returns for equally-weighted and value-weighted portfolios of offshore hedge funds. The data are collected from 1989 to 1995. It is significant to refer that posterior studies proved that there were many problems with biases before 1993.

In the following they maintained that the S&P 500 was not the appropriate benchmark for fund performance because of the nature of hedge fund market neutral positions. So, they used as value-weighted return benchmarks the 10 different strategies of hedge funds. They found positive excess returns for all categories of hedge funds except for short-sellers.

Naik, Ramadorai and Sromqvist (2007) investigated whether capacity constraints at the level of hedge fund strategies have been responsible for the declining of the level of alpha (significant absolute returns) over the period 1995-2004. Before starting with these models, they calculated the Assets Under Management (AUM) and the returns. Firstly, they calculated the dollar flows F_{it} for fund i during month t as follows: $F_{it} = A_{it} - A_{it-1}(1 + r_{it})$. Here A_{it}, A_{it-1} and r_{it} are the AUM for fund i at the end of month t and t-1, and the returns accrued from month t-1 to t respectively. In the following, they computed strategy level flows by aggregating individual fund flows up to the level of strategies and scale the dollar flows by strategy aggregated end of previous month AUM: $f_{st} = \left(\sum_{i=1}^{N_s} F_{it}\right) \Big/ \left(\sum_{i=1}^{N_s} A_{it-1}\right)$. The first step was completed. In the following, they computed value weighted excess return indices for each strategy. Value-weighted excess returns were constructed as $r_{st}^{VW} = \sum_{i=1}^{N_s} \omega_{it}(r_{it} - r_{ft})$, where $\omega_{it} = A_{it-1} \Big/ \left(\sum_{i=1}^{N_s} A_{it-1}\right)$ are AUM weights reconstructed each month, r_{it} is the net of fee return on fund i, a member of strategy s in month t and r_{ft} is the return on the three-month US Treasury bill in month t.

To calculate the systematic component of strategy index returns, they regressed them on factors that have been shown to have explanatory power for hedge fund returns. These factors are drawn from the work of Fung and Hsieh (2004). They applied the following regression: $r_{st} = a_s + X_t b_s + e_{st}$, where, r_{st} is the value-weighted return index for strategy s at time t, b_s is the estimated factor loading for strategy s and X_t is the independent variables which are referred below. The dependent variable in each regression is the AUM weighted (net-of-fee) excess return of hedge funds within a strategy. The independent variables are:

- The excess return on the S&P 500 index (SNPMRF).
- A small minus big factor (SCMLC) constructed as the difference of the Wilshire small and large capitalisation stock indices.
- Three portfolios of lookback straddle options on currencies (PTFSFX), commodities (PTFSCOM) and bonds (PTFSBD), which are constructed to replicate the maximum possible return to a trend-following strategy on the underlying asset, all in excess returns.
- The yield spread of the US ten-year treasury bond over the three-month T-bill, adjusted for the duration of the ten-year bond (BD10RET).
- The change in the credit spread of the Moody's BAA bond over the ten-year treasury bond, also appropriately adjusted for duration (BAAMTSY).

$$X_t = a_t + \beta_1 \times SNPMRF_t + \beta_2 \times SCMLC_t + \beta_3 \times BD10RET_t + \beta_4 \times BAAMTSY_t + \beta_5 \times PTFSBD_t + \beta_6 \times PTFSFX_t + \beta_7 \times PTFSCOM_t + \varepsilon_t$$

They estimated this regression separately for three sub-periods, thus allowing for breakpoints in the relationship between strategy returns and the seven factors. The breakpoints corresponded to the collapse of Long- Term Capital Management in September 1998 and the peak of the technology bubble in March 2000. Finally, the validity of these pre-specified breakpoints was checked using the Chow (1960) test for structural breaks, where the null hypothesis says that there are three distinct periods in the data over which the systematic risk exposures change greatly. They concluded that alpha have decreased at the level of hedge fund strategies in the most recent period from 2000 to 2004.

Afterwards, they applied a single regression for each strategy. Their goal was to explain time-variation in alpha. This time-variation was captured by running a rolling factor regression each month using a 12-month estimation window. So, they applied the following regression: $r_{sw} = a_{sw} + X_w\beta_{sw} + \varepsilon_{sw}$, where the w subscript represents the window over which the rolling regression is run, r_{sw} is the vector of the 12 return observations for strategy s for window w and X_w the matrix of factors over the same window. The regressions result in a series of estimated factor loadings β_{sw} corresponding to each value w.

After running the regression, with each set of estimated factor loadings, they constructed an out-of-sample quantitative measure of hedge fund ability, $alpha\_u_{st}$. After the calculation of this quantity, they regressed $alpha\_u_{st}$ on lagged strategy specific capital flows and three conditioning variables. They controlled for size and using the total AUM contained within the strategy (logarithmic), additionally conditioning on the squared size to control for potential non-linearity in the relationship. Finally, they controlled for the number of funds within a strategy in the prior year, as a proxy for competition between funds in the strategy. They estimated separate regressions for each one of these periods. They also used flows from month t-13 to t-24 to explain $alpha\_u_{st}$ for period t. The regression is the following:

$$alpha\_u_{st} = k_s + \varphi\left(f_{st-13} + \ldots + f_{st-24}\right) + uAUM_{st-12} + \lambda AUM^2_{st-12} + xNumber_{st-12} + \xi_{st}$$

They interpreted a negative value of φ as evidence of capacity constraints in the strategy.

Firstly, they applied the Fung and Hsieh seven factor model alpha conditional on flows. The coefficient on lagged flows was negative and statistically significant. This was true for four out of the eight strategies. They concluded that there was presence of capacity constraints in these strategies. Secondly, they applied the four-factor model alpha conditional on flows (SNPMRF, SCMLC, BD10RET, BAAMTSY). Taken together, their results suggest that capacity constraints existed at the level of hedge fund strategies, and were likely to be a concern for investors going forward.

Alexander and Dimitriu (2004) applied four factor models. The general factor model representation was: $r_{it} = a_i + \sum_{k=1}^{K} \beta_{ik} F_{kt} + e_{it}$, where, r_{it} is the net of fees excess return on fund i during month t, a_i is the risk adjusted performance of fund i over the estimation sample, F_{kt} is the excess return on the k^{th} risk factor over the month t and β_{ik} is the loading of the fund i on the k^{th} risk factor. In order to select the significant factors for each fund a backward selection approach was applied.

Firstly, they applied a two-index model that considers the two main asset classes, US equities and bonds. This was the simplest possible representation of risk factors and was the base case model for their analysis. The indices used to proxy the equity and bond markets were the Wilshire 5000, the Lehman Government/Credit intermediate and the lagged equity index excess returns in the factor model to account for potentially stale prices, the lagged Wilshire 5000. The two-index model explained only 27% of the total variance of fund excess returns.

Secondly, they applied a broad fundamental model including as factors: international equity and bond indices representing US and worldwide markets, investment style factors, commodities and foreign exchange risk factors and other factors representing specific types of non-linear strategies such as market timing, volatility trading and equilibrium trading. They tried to capture the performance of the main traditional asset classes and other factors to model specific types of strategies, such as market timing, volatility trading and equilibrium bases trading models. Specifically, the factors were the following: equity indices (Wilshire 5000, S&P 500 growth and value, SP mid-cap and small-cap to capture differences in equity investment styles, MSCI world index excluding US to account for the investment opportunities as a separate asset class), bond indices (Lehman Government Credit Bond, Lehman High Yield and Lehman Mortgage Backed Securities), the FED trade weighted foreign exchange rate index as a proxy for foreign exchange risk, the GS Commodity index to capture commodity related investment risk factors. They also included in the regressions the squared excess returns of the main indices. They included two factors capturing specific trading strategies: the change in the equity implied volatility index to account for volatility trades and the prices' dispersion as a leading indicator of price equilibrium trading strategies.

Thirdly, they applied a multi-factor model, using the HFR hedge fund indices as factors. Their model explained an overall average of 46% of the variance in fund excess returns. At an individual fund level, 17% of funds have negative and significant alpha, while only 11% of funds have positive and significant alpha.

Fourthly, a statistical factor model using as factors portfolios replicating the first four principal components of the system of all funds' returns. As we referred the intuition behind statistical factor analysis is that if a group of funds use similar strategies in the same markets, their returns should be correlated.

Schneeweis, Kazemi and Karavas (2004) studied the impact of leverage on return measurement (hedge fund risk and return). They began to study this impact because they have observed that while leverage should theoretically not affect the level of risk-adjusted return within a strategy, it is possible that funds attempting higher levels of leverage might trade differently than lower leverage funds. So, it is possible to have an impact to risk-adjusted performance from leverage.

In this paper, the effect of leverage on hedge fund risk and return was analyzed. In brief, results were presented on the level of leverage used in various hedge fund strategies. Results were also provided to show the degree to which leverage, above or below the median fund leverage, determined superior or inferior risk-adjusted performance within a particular hedge fund strategy.

They used six hedge fund categories: convertible arbitrage, equity hedge, event-driven, distressed securities, merger arbitrage and equity market neutral. They used TASS database which provides two fields for leverage: "average leverage" and "maximum leverage". The latter was used only when there was no information about the average leverage.

Leverage could be best understood as the creation of exposure greater in magnitude than the initial dollar amounts posted to an investment. It may was achieved through borrowing, deployment of proceeds from short sales or through the use of derivatives.

Leverage may be presented in various forms:

- Gross Leverage=(Longs +Shorts)/Net Asset Value
- Net Leverage=(Longs-Shorts)/Net Asset Value
- Gross Longs=(Longs)/Net Asset Value

In the following the funds were separated into two sets: those funds that have both leverage information and 39 months of performance information from January 2000 to March 2003 and those that did not have both.

They created two equal-weighted indexes for each sample. In the following they used two statistical tests for comparing the two sample indexes. Firstly, the Welch t-test, the equivalence of means across two samples. Secondly, the K-S test, the equivalence of the entire returns distribution. The null hypothesis indicates the existence of equivalence.

Finally, they concluded that although different hedge fund strategies might use different amount of leverage, within a particular hedge fund strategy, there was little evidence of a significant difference between risk-adjusted performance of above-median and below-median leveraged funds.

Malkiel and Saha (2005) calculated some descriptive statistics for hedge fund strategies and for some market indices. They found that hedge funds characterized by undesirably high kurtosis and that many hedge fund categories have considerable negative skewness. They used a Jarque-Bera (JB) test for the normality of hedge fund returns and they found that the hypothesis of normality was rejected for all the hedge fund categories except managed futures and global macro.

They applied a probit regression analysis where the dependent variable was binary. It took a value of 1 if a fund was defunct and a value of 0 if it was still alive. Their regression had the following formula:

$$\begin{aligned}\text{Probability of fund demise} = \ & a + Q1 + Q2 + Q3 + Q4 + \text{st. dev. for final 12 months} \\ & + \text{peer comparison} + \text{estimated assets} + e\end{aligned},$$

where Ql is the return for the first quarter before the end of fund performance, Q2 is the return for the second quarter before the end of fund performance, Q3 is the return for the third quarter before the end of fund performance, Q4 is the return for the fourth quarter before the end of fund performance, standard deviation for final 12 months is the standard deviation for the year prior to the end of fund performance, peer comparison is the number of times in the final three months the fund's monthly return fell below the monthly median of all funds in the same primary category and the estimated assets are assets of the fund (in billions of dollars) estimated at the end of performance (if estimated assets were missing for the final month, the first available amount of estimated assets in the final four months was used).

They, finally, concluded that the coefficient of returns relative to peers was statistically significant. The coefficient of "standard deviation for final 12 months" was highly significant which means that higher volatility of return apparently increases the probability of a fund's demise. The coefficient of size was negative and highly significant, so they concluded to the result that a larger fund had a lower probability of exiting.

Ibbotson and Chen (2006) created hedge funds returns free from biases (chapter two). Furthermore, they used the equally-weighted index using the live and dead funds without backfilled data. They also constructed indexes for each of 10 hedge fund subcategories (convertible arbitrage, emerging market, equity market neutral, event driven, fixed income arbitrage, global macro, long/short equity, managed futures, dedicated short and funds of hedge funds). They maintained the constraint that all style weights sum to one. They allowed individual style weights to be negative or above one to account for shorting and leverage. They also included lagged betas as well as contemporaneous betas to control for the stale pricing impact on hedge fund returns. The benchmarks used in the return-based analysis are the S&P 500 total returns (including both concurrent and with one-month lag), U.S. Intermediate-term Government Bond returns (including one-month lag), and cash (U.S. Treasury Bills).

Finally, they found that the alpha of the equally weighted sample was 3.04%. All ten subcategories of types of funds had positive alphas, and the index and five of the subcategories were statistically significant. In general, when combined with stock, bond, and cash portfolios, hedge funds add positive alpha and excellent diversification.

French and Ko (2006) investigated the determinants of hedge fund portfolio performance when hedge funds exhibit security selection skill and market-timing skill. They employed the Treynor and Mazuy (1966) quadratic model to account for nonlinearities. So, they applied the following model: $r_p = a_p + \beta_p r_m + \gamma r_m^2 + \varepsilon$, where r_p is the portfolio return, a_p is the intercept of the regression, β_p is the regression coefficient, r_m is the market return and γ is a market-timing ability coefficient (positive if manager has market timing skill). They used F-statitistic on the regression to find the fitted model and t-statistic on the quadratic term to test if this coefficient was statistically significant. To account for illiquidity they incorporated the Scholes and Williams (1977) nonsynchronous data model $r_p = a_p + \beta_p r_m + \beta_p r_{m-1} + \beta_p r_{m-2} + \beta_p r_{m-3} + \gamma r_m^2 + \gamma r_{m-1}^2 + \gamma r_{m-2}^2 + \gamma r_{m-3}^2 + \varepsilon$. Specifically, they included both contemporaneous and three lagged months as independent variables. They concluded that before and after adjusting for illiquidity, they found strong evidence of security selection skill and limited evidence of market-timing skill.

4.3 Fund factors

When we are referred to return factors, we mean market or macro-factors, which are the market indices, and fund of micro-factors. Hedge funds are affected by these factors. Fund factors are the specific characteristics of individual funds.

4.3.1 Size of the fund

As we refer above, many authors studied the relationship between size of the fund and performance. Firstly, the size of a fund is the total amount at the start of the calculation period. Many studies have shown that the relationship between size of the fund and performance helps investors to optimize future profits and for hedge fund manager to decide when it is appropriate to close the fund to new investments.

Gregoriou and Rouah (2002) tested the relation between fund's size and fund's return using Pearson's correlation coefficient and Spearman's rank correlation, the Sharpe ratio and the Traynor ratio, they found that funds' size was not affect hedge funds' performance.

Koh, Koh and Teo (2003) study this relationship for Asian hedge funds. Their results corroborate the previous results, with a non-significant relationship.

De Souza and Gokcan (2003) exhibited through a regression on the TASS database that assets under management have a positive relationship with performance. According to them, this could imply that poor performing funds have difficulty attracting new contributions, or that large size allows lower average costs to be obtained.

Amenc, Curtis and Martellini (2003) computed, for each fund, the average assets over the time interval which they used. In the following, they divided the funds into two equal-size groups: those in the larger half in asset size and those in the smaller half. For each group, they computed the average alpha obtained with each of the following methods: the standard CAPM, an adjusted CAPM for the presence of stale prices and an implicit factor model extracted from a Principal Component Analysis. When they obtained alphas, they performed a two-sample t-test to determine the significance of the differences. They concluded that the mean alpha for large funds exceeds the mean alpha for small funds. This fact, combined with the observation that most of the results were statistically significant, suggests that large funds did indeed outperform small funds on average.

Agarwal, Daniel and Naik (2003) and Goetzmann, Ingersoll and Ross (2003) found positive and concave relationship between returns and assets. In this occasion, they did not analyze the relationship for different hedge fund categories such as Getmansky (2004) did. Categories that hold illiquid assets, have limited market opportunities and high market impact of trades, are more likely to exhibit the concave relationship.

4.3.2 Age of the fund

Fund age is defined as the length of time in operation prior to the beginning of any study.

Howell (2001) investigated the relationship between the age of hedge funds and their performance from 1994 to 2000. The first step was to adjust the returns by applying the probabilities of failure to report to the surviving funds. This gives *ex-post* returns, which correspond to the true costs and benefits of investing in funds with different maturities. The second step was to adjust the returns by applying the probability of future survival to the survivors' returns by age deciles. This gives *ex-ante* returns, which are the expected returns from investing in hedge funds with different maturities. *Ex-ante* returns infer that young funds' returns are superior to those of seasoned funds: the youngest deciles exhibits a return of 21.5%, while the whole sample median exhibits a return of 13.9% (a spread of 760 basis points in favour of young funds). Moreover, the spread between the deciles of youngest funds and the deciles of oldest funds is 970 points, and the spread between the second youngest fund deciles and the whole sample median is 290 points. The conclusion of this study was that hedge fund performance deteriorates over time, even when the risk of failure was taken into account. Consequently, the youngest funds seem particularly attractive.

Amenc, Curtis and Martellini (2003) divided the funds into two groups of approximately equal size: newer funds (age of one or two years) and older funds. For each group, they computed the average alpha obtained with each of the methods discussed earlier and performed a two-sample t-test to determine the significance of the differences. They concluded that for all methods, the mean alpha for newer funds exceeds the mean alpha for older funds. It is important to refer that the differences vary in significance across the methods. The most significant results are obtained with the CAPM and Explicit Factor models.

Koh, Koh and Teo (2003) found that fund age is not an explanatory factor for Asian hedge fund returns in a cross-sectional Fama and MacBeth (1973) framework.

De Souza and Gokcan (2003), applied multifactor models and they concluded that older funds outperform younger funds on average.

4.3.3 Manager tenure

Boyson (2003) analysed the relationship between hedge fund manager tenure and fund returns. As far as the manager tenure was concerned, regressions showed that each additional year of experience was associated with a statistically significant decrease in the annual returns of approximately -0.8%. To explain the relationship between experience and performance in the light of risk-taking behaviour, he successively examined the relationship between manager tenure and risk taking behaviour and the relationship between risk-taking behaviour and returns. Focusing on the relationship between manager tenure and risk-taking behaviour, three risk measures are used: the standard deviation of a portfolio's return, a tracking error and a beta. It appeared that an increase in manager tenure, fund size or tenure/size interaction engenders less risky behaviour. Concerning the relationship between the risk-taking behaviour and the returns, each of the three risk measures was positively related to the annual returns. In other words, when manager tenure increases, risk-taking decreases, and when risktaking decreases, returns decrease. These results highlighted the impact on hedge fund returns of increasing career concerns over time, with risk-taking behaviour characterised by increasing risk aversion. Career concerns in the hedge fund industry are unique in that they change over time. This is due to the sources of the manager's compensation, i.e. the assets under management and the returns. Young managers generally have a lower level of assets under management than older managers. Consequently, they take more risk to obtain good returns, while the large size of the fund provides older managers with their compensation. As a result, the risk level diminishes as the hedge fund manager's age rises. Moreover, statistics show that failed hedge fund managers rarely start a new hedge fund, and if they move into the mutual fund industry, for example, this is associated with a pay cut. The amount of the pay cut is more significant for older hedge fund managers, and it is thus an incentive for them to mitigate their risk-taking behaviour. A final explanation for the lower level of risk taken by an older hedge fund manager is the large amount of personal assets invested in the fund.

4.3.4 Performance fees

In this occasion, we investigate the impact of incentive fees paid to the fund manager on fund performance.

Kazemi, Martin and Schneeweis (2002) studied the impact of performance fees for value, growth and small styles. From their data, fees had a poor effect on performance.

Koh, Koh and Teo (2003) found that funds with higher performance fees have smaller post fee returns than funds with lower performance fees.

De Souza and Gokcan (2003) found that incentive fees and performance were positively correlated. Higher incentive fees generating higher performance can be explained by the fact that incentive fees are increased when a manager improves his performance or by the fact that the best managers in terms of performance demand higher incentive fees.

Amenc, Curtis and Martellini (2003) for each fund, they obtained the incentive fees, expressed as a percentage of profit. They then divided the funds into two groups: those with incentive fees >=20% (most were exactly 20%) and those with incentive fees < 20%. For each group, they computed the average alpha obtained with each of the methods, which we have refered above. In the following they performed a two-sample t-test to determine the significance of the differences. They concluded that the mean alpha for high incentive funds exceeds the mean alpha for low incentive funds. They had also investigated the impact of a fund’s administrative fees on performance by dividing the funds into two groups: those with administrative fees >= 2% and those with fees< 2%. They concluded that there was no significant difference between funds with higher or lower administrative fees.

4.3.5 Combination of fund factors

Liang (1999) used a cross-sectional regression of average monthly returns on fund characteristics. Specifically, he used the following model:

$$R_i = a_{0i} + a_{1i}(IFEE) + a_{2i}(MFEE) + a_{3i}(LN(ASSETS)) + a_{4i}(LOCKUP) + a_{5i}(AGE)$$

where IFEE is the incentive fee in percentage, MFEE is the management fee in percentage, LN(ASSETS) is the natural logarithm of fund assets, LOCKUP is the lockup period in number of days, AGE is total number of months since inception, R_i is the monthly return for fund i.

He concluded that high incentive fee was indeed able to align the manager's incentive with fund performance. He also found that successful funds attract more money and the longer the lockup period the better the fund performance and finally management fee did not affect the fund performance. In conclusion, they found that if fund's age is big then it is possible to reduce the average monthly return.

Koh, Koh and Teo (2003) found that Asian hedge funds returns had a positive and significant relationship with the redemption period and the size of the holding company.

Kazemi, Martin and Schneeweis (2002) found that the redemption period seems to affect the returns, since for a similar strategy; funds with a quarterly lockup had higher returns than funds with a monthly lockup.

De Souza and Gokcan (2003) exhibited that the investment by a manager of his own capital had a positive impact on performance, like the lockup and redemption periods.

Ackerman, Mc Enally and Ravenscraft (1999) attempted to isolate hedge fund characteristics that might explain the performance and volatility of hedge funds. They regressed risk-adjusted performance and volatility on four characteristics and six dummy variables for hedge fund categories. Firstly, they adjusted for total risk by using the Sharpe ratio. In the second regression they applied the natural log of the standard deviation of the hedge fund total monthly over the 2-,4-,6- and 8-year time periods. The first hedge fund characteristic was incentive fee, which was statistically significant in all four time periods for the Sharpe ratio regressions. In the volatility regression it was not statistically significant. The second hedge fund characteristic was management fee. In the first type of regressions they found that the coefficient was negative and statistically significant only in one of the four regressions and in the second type of regressions, they found that it was statistically positive. The other hedge fund characteristics were not statistically significant, so these did not play important role in performance evaluation. Others fund characteristics: age, U.S vs offshore where have a value of one for U.S domiciled funds and zero for offshore funds and fund categories, like event driven, funds of funds, global, neutral market, short sales and U.S opportunistic which they have value of one if a funds is in the specified category and zero otherwise.

Edwards and Caglayan (2001) applied a six factor model, which involved fund factors like age and size of the fund. They examined whether hedge funds that employ attractive incentive fees to compensate fund managers perform better than funds that pay less attractive incentive fees. So, they applied the following model:

$$R = a + b_1(\text{Moderate Incentive Fee}) + b_2(\text{High Incentive Fee}) + b_3(\text{Size}) + b_4\left(\frac{1}{\text{Size}}\right)$$
$$+ b_5(\text{Age}) + b_6(\text{Management Fee}) + e$$

High Incentive fee: incentive fees of 20% or higher.

Moderate Incentive fee: incentive fees between 2% and 20%.

They also used the reciprocal of size to capture nonlinearity in the size-performance relationship.

They found that incentive fee is positively related to excess returns for all hedge funds taken together and all investment styles. They also found that a positive coefficient on the size variable with a negative coefficient on the size reciprocal variable indicates that hedge fund performance increased at a declining rate as fund size increases. Age appears to be a significant explanatory factor only for global, global macro and market neutral funds. Management fee was not statistically significant.

Do, Faff and Wickramanayake (2005) estimated a cross-sectional regression model, where the dependent variable is the Australian hedge funds returns proxied in two alternative ways: conventional Sharpe ratio and modified Sharpe ratio. They used as independent variables, age (months), holding period (the number of days that investor have to give notice to a fund before a redemption can take place), incentive fee (%), management fee (%), size (natural log) and float (a dummy variable for benchmark factor measurement, that takes a value of 1 when a fund has a floating benchmark and zero if a floating benchmark is not specified or it has no floating benchmark).

They, also, estimated a cross-sectional regression model, where the dependent variable is the Australian hedge funds risk proxied in two alternative ways: standard deviation of returns and factor loading beta. They used the same independent variables with the first model. Finally, they observed that Australian hedge fund returns are positively related to incentive fees and negatively related to management fees. Fund age is found to have a positive relationship with the level of risk measurements (standard deviation and factor loading beta) and incentive fee have a positive relationship only for standard deviation analysis.

CHAPTER FIVE

PERFORMANCE PERSISTENCE

5.1 Introduction

Performance persistence is an interesting and essential measure. It is commonly known that investors invest to different hedge funds on the basis of their track record. It becomes coherent that hedge fund investors are interested for the stability of hedge funds' performance. There are two test methods for the calculation of the performance persistence. The first method refers to measuring the persistence of relative returns, where the funds can be ranked in comparison to the median return in a given period or to be ranked into deciles based on the previous sub-period return and the second measures the persistence of individual returns directly, without a comparison to a median.

5.2 Persistence of relative returns

This method has two expressions. It is distinguished in a two-period framework and in a multi-period framework.

5.2.1 Two period framework

This method has two main directions. Non-parametric and parametric methods.

5.2.1.1 Non-parametric methods

We are based on the construction of a two-way winner and loser contingency table. Winners are funds whose returns is higher than the median returns of all the funds following the same strategy over this period and losers are funds whose alpha is weaker than the median return of all the funds following the same strategy. Consequently, persistence refers to funds which are winners over two consecutive periods, denoted WW and funds which are losers over two consecutive periods, denoted LL. In the absence of persistence, winners during the first period and losers during the second period will be denoted WL and LW if the opposite is the case. Non-parametric methods have several important tools which are used for the calculation of the performance persistence.

- Cross Product Ratio test

The numerator of CPR corresponds to the funds which persist and the denominator corresponds to the funds which do not persist: $CPR = (WW * LL)/(WL * LW)$.

Under the null hypothesis of no persistence, the ratio is equal to 1. The statistical significance of CPR is tested via the calculation of the Z-statistic, corresponding to the ratio of the natural logarithm of the CPR to the standard error of the natural logarithm of CPR, expressed as follows: $Z\text{- statistic} = \ln(CPR)/a_{\ln(CPR)}$, where $a_{\ln(CPR)}$ is the standard error of the natural logarithm of CPR equal to: $a_{\ln(CPR)} = \sqrt[2]{\frac{1}{WW} + \frac{1}{LL} + \frac{1}{WL} + \frac{1}{LW}}$.

- Chi-square test

The chi-square test is carried out by comparing the distribution of the observed frequencies for the four categories WW, LL, WL and LW with the expected frequencies of the distribution. The chi-square measurement allows the level of independence of the results to be evaluated between two periods. It is then possible to construct, for each sub-period, different rankings according to the number of years. The chi-square is equal to: $x^2 = \varepsilon\ (O_i - E_i)^2/E_i$, where O_i is the observed number of funds in each case of the contingency table, and E_i is the expected number of funds in each case.

Park and Staum (1998) collected data from TASS database for the period 1986-1997, they used appraisal ratio in a two-period test. They found performance persistence at an annual horizon but the strength of the persistence seems to vary substantially from year to year.

Edwards and Caglayan (2001) applied non parametric method and they found that the existence of both winner and loser persistence at the 5% significance level or better for all hedge funds and for funds of funds, global-macro funds and market-neutral funds.

Capocci and Hubner (2004) followed the methodology of Carhart (1997) using his combined model. All funds were ranked based on their previous year return. Every January, they put all funds into 10 equally weighted portfolios, ordered from highest to lowest past returns. Portfolios 1 (high) and 10 (low) were then further subdivided on the same measure. The portfolios were held till the following January and then rebalanced again. This yielded a time series of monthly returns on each decile portfolio from 1/1994 to 6/2000. Funds that disappeared during the course of the year were included in the equally weighted average until their death, then portfolio weights were readjusted appropriately. They concluded that best performing funds followed momentum strategies whereas worst performing ones might follow momentum contrarian strategies, best performing funds did not invest significantly in emerging market bonds, average return funds preferred high book-to-market stocks, whereas best and worst performing ones might prefer low book-to-market ones, no persistence in performance existed for best and worst performing funds, but there was weak evidence of persistence for middle deciles, where some funds significantly beat the market with persistence. Evidence was more pronounced for the 1985–1993 period, but it was likely to be driven by the absence of dissolved funds in this period.

Kat and Menexe (2002) worked with monthly net-of-fee hedge fund return data taken from TASS database. They classified funds in the following hedge fund strategies: long/short equity, event driven, global macro, emerging markets, relative value and fund of funds. They also used the S&P 500 index as a proxy for stocks and the Salomon Brothers 7- year Government Bond index as a proxy for bonds.

They used two-winners contingency table and they found that the CPRs for the mean, with the exception of emerging markets and relative value, were close to 1, with none of them statistically significant. So, there was no evidence of persistence in mean returns. They found much more persistence in the standard deviations. In this case, the CPRs were extremely highly and statistically significant. Apart from long/short equity and funds of funds, the CPRs for skewness were all close to 1. We had the same for kurtosis. Furthermore, apart from long/short equity, they found little or no persistence in the correlation with bonds, but there was significant persistence in the correlation with stocks.

- Spearman rank correlation test

It is a distribution free method. Assume a set of funds (1, 2, 3,..., n), which have been ranked by two different periods (*x* and *y*). Let $x(i)$ and $y(i)$ be the rank (rank one is the highest and rank *n* is the lowest) of fund *i* in the two different periods respectively and define $d_i = x(i) - y(i)$ as the distance between these rankings.

$$r_s = 1 - 6 \times \left(\left(\sum_{i=1}^{n} d_i^2 \right) \Big/ \left(n^3 - n \right) \right).$$

The result will always be between 1 (a perfect positive correlation, i.e. a perfect positive persistence of the performance) and minus 1 (a perfect negative correlation, i.e. a perfect negative persistence of the performance). A coefficient close to 0 indicates an absence of performance persistence over two periods.

Park and Staum (1998) used this method and they found performance persistence at an annual horizon with the same variability in the strength of persistence.

Brorsen and Harri (2002) used the Spearman rank correlation and they found significant levels of persistence are found for all styles considered as a group, market neutral, event driven, short sales and funds of funds, contrary to sector and long only styles. Nevertheless the authors explained these opposite conclusions by the possibly low power of the Spearman test in the context of the performance persistence tests.

5.2.1.2 Parametric methods

The return of the current period (explained variable) is regressed onto the return of the previous period (explanatory variable). In other words, returns are regressed against lagged returns. A positive coefficient applied to the explanatory variable indicates that a hedge fund that performs well over the previous period will also obtain a positive result at the time of the current period, which would testify to performance persistence. Specifically, if the estimated slope coefficient is significantly greater than zero, then this is evidence of persistence.

Edwards and Caglayan (2001) applied regressions with 1-year and 2-year selection and performance-period alphas during the 1990–1998 periods to determine if past performance is a predictor of future performance. Specifically, for 1-year selection and 1-year performance periods, eight separate cross-section regressions were estimated during the 1990–1998 period and for 2-year selection and 2-year performance periods, six separate cross-section regressions were estimated. Persistence was considered to exist if the estimated slope coefficients in these equations were significantly greater than zero. The results of this test were similar to those obtained from the two way winner-and-loser contingency analysis. These results support the conclusion that there was persistence in hedge fund performance among both winners and losers. The estimated regressions had the following formula:
Performance-period-six-factor-analysis=a+bSelection-six-factor-alphas+e.

Boyson and Cooper (2004) used a multi factor model to control for common risk factors in hedge fund performance. This model has the following formula: $r_{pt} = a_{pT} + \sum_{k=1}^{K} b_{pkT}F_{kt} + \sum_{d=1}^{D} b_{pdT}H_{dt} + \varepsilon_t$, where r_{pt} is portfolio p's return in month t in excess of the risk-free rate (t=1 to T months), F_{kt} are each of the passive index returns (US Trade Weighted Dollar index, Lehman Brothers 30-year Treasury bond, US Aggregate Bond and the Value Weighted CRSP index and (HML, SMB and MOM) in month t and the

H_{dt} are each of the hedge fund index returns (convertible arbitrage, dedicated short bias, emerging markets, equity market neutral, event driven, fixed income arbitrage, global macro, long/short equity, managed futures) in month t.

With this regression, they studied the quarterly persistence analysis when funds are selected based on prior performance. Hedge funds were sorted at the beginning of each quarterly period from the second quarter in 1994 to the final quarter in 2000 into decile portfolios based on their previous quarter's return (lagged returns) less the risk-free rate. The portfolios were equally weighted quarterly so the weights were readjusted whenever a fund disappears. Funds with the highest past quarterly returns in excess of the risk-free rate comprised decile 10 and funds with the lowest past quarterly returns comprised decile 1. The dependent variable is the portfolio's excess monthly return. They found that for the lagged decile portfolios, average monthly returns were fairly monotonic, increasing from -0.66% for decile 1(worst) to 0.49% for decile 10 (best). Examining the alphas from the regressions, the intercept on the best minus worst (10-1) portfolio was positive but not statistically significant. So, there was no evidence of quarterly persistence.

In the following, they studied the quarterly persistence analysis when funds were selected based on prior performance and manager tenure (the length of time that the manager has been overseeing the fund). Hedge funds were sorted at the beginning of each quarter from the second quarter in 1994 to the final quarter in 2000 into thirds portfolios based on their previous quarterly return (lagged returns) less the risk-free rate. The portfolios were equally weighted quarterly so the weights were readjusted whenever a fund disappears. These portfolios were then cross-sorted based on the quarter-end value of manager tenure into three additional portfolios: young, middle, and old. There were nine portfolios (portfolio 1=worst, portfolio 9=best), ranging from poor and old to good and young. A tenth portfolio was created which is long the good and young managers and short the poor and old managers. The dependent variable is the portfolio's monthly return in excess of the risk-free rate. The independent variables were the passive and hedge fund indices.

They concluded that the intercept from the 9-1 portfolio was positive and significant at the 5% level. The annualized excess return from investing in this portfolio was about 9% per year, which was significant as well. It appeared that poor performance among old, past bad managers is driving in the evidence of quarterly performance persistence.

Brown, Goetzmann and Ibbotson (1999) found no persistence in raw and risk-adjusted returns at an annual horizon. It should be noted that the database only contains offshore funds and it is probably that there was significant problem with biases because the data are from 1989.

Agarwal and Naik (2000) used parametric tests (cross-sectional regression) and non-parametric tests (CPR and Chi-square test) in a two-period framework and Kolmogorov-Smirnov goodness-of-fit test in a multi-period framework. They collected data from HFR (1982-98). Firstly, they used quarterly and half-yearly returns combined with alpha and the appraisal ratio as a performance measure. All these methods showed significant performance persistence in pre-fee and post-fee retruns. We received the same results al long as it concerns in the non-directional and directional strategies. In the multi-period framework they found that persistence is presented in losers and no in winners at half-yearly returns.

Brorsen and Harri (2002) conducted regression-based tests which indicated significant persistence for all styles (except short sales) for one-month, two-month and three-month horizons. For longer horizons the significance decreases, and the lagged values become negative after 11 months.

Baquero, ter Horst and Verbeek (2002) found in raw returns and at a quarterly horizon, positive persistence in hedge fund returns, particularly for the best four deciles. In order to check whether the presence of a cross-sectional variation in expected returns due to style or risk characteristics explains the observed persistence patterns in raw returns, persistence in relative returns is examined. On a risk-adjusted basis, at a quarterly horizon, strong persistence of the relative returns is found.

They showed that in raw returns, at the annual horizon, the top three deciles showed persistence. On a risk-adjusted basis, at an annual horizon, a strong persistence of the relative returns to style benchmarks for the top three deciles.

Chen and Passow (2003) examined, through cross-sectional regressions (for this purpose, the track record from January 1990 to September 2002 is split into two sub-periods of equal length), the performance persistence of hedged equity funds. More accurately, the persistence of selected funds was compared to the persistence of the other funds. The selected funds were those which maintain a moderate exposure to the factors of a multi-factor model. These funds exhibited better performance persistence. On the other hand, they showed that outperformers did not show significant performance persistence.

5.3 Multi-period framework, K-S Goodness-of-fit test

The Kolmogorov-Smirnov test (K-S test) tries to determine whether two data sets differ significantly. A multi-period test has the advantage of proposing a more marked robustness of the results.

The Kolmogorov-Smirnov test is a goodness-of-fit test to a continuous law, which takes all of the quantiles into account. The model is a sample (X1,...,Xn) of an unknown law P. The Kolmogorov-Smirnov test is defined by Ho: the data follows a specified distribution, and H1: the data does not follow a specified distribution.

To apply the Kolmogorov-Smirnov test, the cumulative frequency (normalized by the sample size) of the observations is calculated as a function of class. Then the cumulative frequency for a true distribution (most commonly, the normal distribution) is computed. The greatest discrepancy between the observed and expected cumulative frequencies, which is called the "D-statistic", has to be found. Finally it is compared to the critical D-statistic for that sample size.

In the context of the performance persistence of hedge funds, this test is used in order to check whether the distributions of winning funds and losing funds are statistically different from the theoretical distribution. Observed frequencies of wins and losses are recorded. This frequency distribution is compared with that generated from a normal distribution and the maximum difference in cumulative densities between the observed and the normal distribution is used to construct the Kolmogorov-Smirnov statistic.

An attractive feature of this test is that the distribution of the K-S test statistic itself does not depend on the underlying cumulative distribution function being tested. Another advantage is that it is an exact test (the chi-square goodness-of-fit test depends on an adequate sample size for the approximations to be valid). The K-S test is generally more efficient than the chi-square test for goodness-of-fit for small samples and can be used for very small samples where the chi-square test does not apply.

Despite these advantages, the K-S test has the following important limitation: it can only be applied to continuous distributions.

CHAPTER SIX

AUTOREGRESSIVE CONDITIONAL HETEROSKEDASTICITY MODELS

6.1 Introduction

Until a decade ago, the focus of most macro econometric and financial time series modeling centered on the conditional first moments. The increased importance played by risk and uncertainty considerations in modern economic theory, however, have necessitated the development of new econometric time series techniques that allow for the modeling of time varying variances and covariances.

Parallel to the success of standard linear time series models, arising from the use of the conditional versus the unconditional mean, the key insight offered by the ARCH model lies in the distinction between the conditional and the unconditional second order moments.

Linear models as time series models can not explain some important empirical regularities of asset returns. One of these regulatories is leptokurtosis, which is the tendency of financial asset returns to have distributions that exhibit fat tails and excess peakedness at the mean. Furthermore, in financial markets large changes tend to be followed by large changes and small changes tend to be followed by small changes. This phenomenon is called volatility clustering or conditional heteroskedasticity, which is immediately apparent when asset returns are plotted through time. Another feature of asset returns is called leverage effect and refers to the tendency for changes in stock prices to be negatively correlated with changes in stock volatility. Non-trading periods is another feature which represents the information that accumulates when financial markets are closed and is reflected in prices after the markets reopen. It is significant to add that Fama, French and Roll (1992) concluded that information accumulates more slowly when the markets are closed than when they are open.

To deal with volatility, we use the class of univariate autoregressive conditional heteroskedasticity (ARCH) models, which are capable of modeling time varying volatility and capturing many of the stylized facts of the volatility behavior, which are usually observed in financial time series. By postulating the time-varying volatility to be a function of the current information set, these models are able to model the periods of relative tranquility followed by bursts of extreme values often present in stock market series.

Two of the most useful ARCH parameterizations are the generalized ARCH (GARCH) model introduced by Bollershev (1986) and the exponential GARCH (EGARCH) model suggested by Nelson (1991).

6.2 ARCH model

Engle (1982) presented the ARCH model in 1982 and created a field of many financial applications in the future. This model provides a systematic framework for volatility modeling. The basic idea of the ARCH models is that the errors ε_t are not autocorrelated, but dependent and the dependence of ε_t can be described by a simple quadratic function on its lagged values.

Specifically, an ARCH(m) model assumes that $\varepsilon_t = \sigma_t z_t$, $\sigma_t^2 = a_0 + a_1\varepsilon_{t-1}^2 + ... + a_m\varepsilon_{t-m}^2$, where $\{z_t\}$ is a sequence of independent and identically distributed random variables with mean zero and variance 1, $a_0 > 0$ and $a_i \geq 0$ for $i > 0$. The coefficients a_i must satisfy some regularity conditions to ensure that the unconditional variance of a_t is finite. z_t is often assumed to follow the standard normal or a standardized student-t distribution.

From the structure of the model, it is obvious that large past squared residuals $\{\varepsilon_{t-1}^2\}_{i=1}^{m}$ imply a large conditional variance of σ_t^2 for the errors ε_t. This means that, under the ARCH framework, large shocks tend to be followed by large shocks.

We mention that the ARCH model assumes that positive and negative shocks have the same effects on volatility, because it depends on the square of residuals the previous shocks. In practice, it is well known that the price of a financial asset responds differently to positive and negative shocks. Additionally, the ARCH model does not provide any new insight for understanding the source of variations of a financial time series. It only provide a mechanical way to describe the behavior of the conditional variance. Finally, ARCH models are likely to overpredict the volatility because they respond slowly to large isolated shocks to the return series.

6.3 GARCH model

The ARCH model often requires many parameters to adequately describe the volatility process of an asset return. Bollershev (1986) proposes a useful extension, known as the generalized ARCH (GARCH) model. For a log return series r_t, we assume that the mean equation of the process can be adequately described by an ARMA model. Let $\varepsilon_t = r_t - \mu_t$ (conditional mean equation) be the mean-corrected log return. Then ε_t follows a GARCH(m,s) model if $\varepsilon_t = \sigma_t z_t$, $\sigma_t^2 = a_0 + \sum_{i=1}^{m} a_i \varepsilon_{t-i}^2 + \sum_{j=1}^{s} b_j \sigma_{t-j}^2$ (conditional variance equation), where σ_t^2 is the conditional variance of the $\{\varepsilon_t\}$ process at time t; again $\{z_t\}$ is a sequence of iid random variables with mean 0 and variance 1, $a_0 > 0$, $a_i \geq 0$ and $b_j \geq 0$. These restrictions ensure a positive variance. Stationary conditions impose that $\sum_{i=1}^{\max(m,s)} (a_i + b_i) < 1$. It is understood that $a_i = 0$ for $i > m$ and $b_j = 0$ for $j > s$. The latter constraint on $a_i + b_i$ implies that the unconditional variance of ε_t is finite, whereas its conditional variance σ_t^2 evolves over time. As before, z_t is often assumed to follow a standard normal or a standardized student-t distribution. This equation $\sigma_t^2 = a_0 + \sum_{i=1}^{m} a_i \varepsilon_{t-i}^2 + \sum_{j=1}^{s} b_j \sigma_{t-j}^2$ reduces to a pure ARCH(m) model if s=0.

The strengths and weaknesses of GARCH models can easily be seen by focusing on the simplest GARCH(1,1) model with $\sigma_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + b_1 \sigma_{t-1}^2$,

$0 \le a_1,\ b_1 \le 1,\ (a_1 + b_1) < 1$. Usually, a GARCH(1,1) model with only three parameters in the conditional variance equation is adequate to obtain a good model fit for financial time series.

6.4 EGARCH model

EGARCH was proposed by Nelson (1991) and it has the following formulation: $\log\left(\sigma_t^2\right) = \alpha_0 + \sum_{i=1}^{p} \alpha_i \left(\theta \frac{\varepsilon_{t-i}}{\sigma_{t-i}} + \gamma \left[\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| - E\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right|\right]\right) + \sum_{j=1}^{q} \beta_j \log\left(\sigma_{t-j}^2\right)$.

With the application of this model, we achieved to model $\log\left(\sigma_t^2\right)$ in order to ensure that σ_t^2 will be positive, even if the parameters are negative. The application of this model gives us the advantage to avoid setting artificially non-negativity constraints on the model parameters. In regard to asymmetries if the relationship between volatility and returns is negative, γ (negative shocks=bad news), will be negative.

6.5 PGARCH model

Ding, Granger and Engle (1993) proposed a special case of GARCH models, the power GARGH or PGARCH model. It has the following expression: $\sigma_t^d = a_0 + \sum_{i=1}^{p} a_i \left(\left|\varepsilon_{t-i}\right| + \gamma_i \varepsilon_{t-i}\right)^d + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^d$, where d is a positive number and γ_i is the coefficient of leverage effect. It is important to mention that if we place d=2, then we take the basic GARCH model. Usually, researchers place d=1 because in this occasion the GARCH model is robust to outliers.

6.6 GARCH-M model

The GARCH-M model was created by Engle, Lilien and Robins (1987) in order to cover the financial expectations of investors, who take additional risk to gain higher expected returns. The return of an asset may depend on its volatility. To model such a phenomenon, one may consider the GARCH-M model, where 'M' stands for GARCH in mean. A simple GARCH(1,1)-M model can be written as $r_t = \mu + c\sigma_t^2 + \varepsilon_t$, $\varepsilon_t = \sigma_t z_t$ and $\sigma_t^2 = a_0 + a_1\varepsilon_{t-1}^2 + b_1\sigma_{t-1}^2$, where μ and c are constant. The parameter c is called the risk premium parameter. A positive and statistically significant c indicates that the return is positively related to its past volatility (conditional variance) and it leads to a rise in the mean return.

6.7 GJR or TGARCH (Thershold GARCH)

The GJR model, which was proposed by Glosten, Jaganathan and Runkle (1993), is a simple extension of GARCH with an additional term added to account for possible asymmetries. Specifically, the positive and negative innovations are let to have different impact on the conditional variance. The conditional variance is given in the general form by $\sigma_t^2 = a_0 + \sum_{i=1}^{p} a_i\varepsilon_{t-i}^2 + \sum_{j=1}^{q} b_j\sigma_{t-j}^2 + \sum_{i=1}^{p} \gamma_i S_{t-i}\varepsilon_{t-i}^2$, where $S_{t-i} = \begin{cases} 1, \text{ if } \varepsilon_{t-i} < 0 \\ 0, \text{ otherwise} \end{cases}$. For a leverage effect, we could see $\gamma > 0$. The condition for non-negativity will be $a_0 \geq 0$, $a_1 \geq 0$, $b \geq 0$ and $a_1 + \gamma \geq 0$.

CHAPTER SEVEN

APPLICATION

7.1 Introduction

We have the monthly returns of ten hedge funds and the monthly returns of 14 pricing factors. Our aim is to conclude in eight top deciles portfolios. Specifically, we apply, for each hedge fund, a single factor, the Fama and French three-factor and the Carhart four factor model. We also apply a multifactor model at which the market indices are, suitably, selected from the backward selection approach. We select the best two performing hedge funds, from each model and for all ten hedge funds. The data from the last year of each hedge fund is used in the out-of-sample analysis.

In the following, we observe the existence of autocorrelation and volatility clustering, or conditional heteroskedasticity, applying Ljung-Box tests in the standardized residuals and the same test in the squared standardized residuals, which can not be explained by linear or time series models. To deal with volatility, we use the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models on the foresaid models. These models capture time varying volatility and many of the stylized facts that are observed in financial time series. It is known that the efficiency in parameter estimation and the accuracy in interval forecast can be improved by modeling the volatility of a time series.

7.2 Detection of autocorrelation

We plot the monthly returns of the ten hedge funds (Figure 7.1). We can conclude that both large changes and small changes are clustered together, which is typical of many high frequency macroeconomic and financial time series.

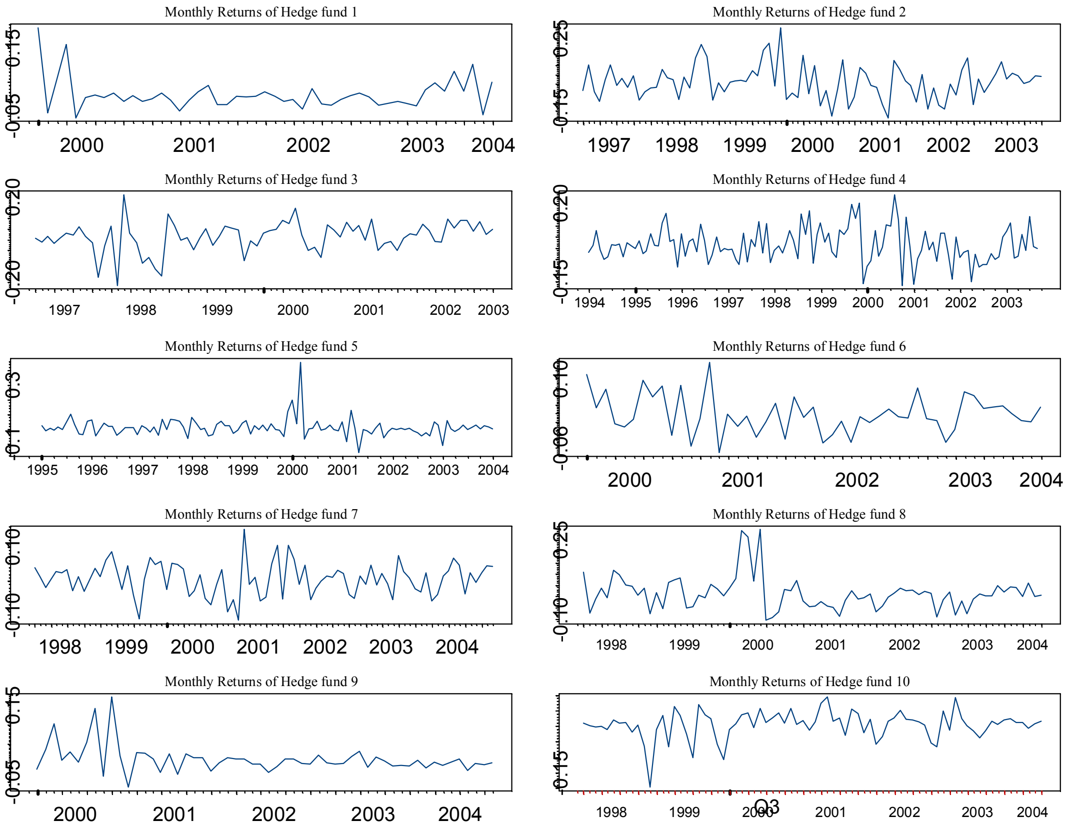


Figure 7.1: Plot for all monthly hedge funds returns.

To confirm this conjecture, we construct the autocorrelation plots of the monthly returns of the ten hedge funds and their monthly squared returns (Figure 7.2). Obviously, there is autocorrelation in the return series of hedge fund 1 up to lag 3, of hedge fund 3 and 4 up to lag 9 and hedge fund 8 up to lag 2, while the squared returns exhibit significant autocorrelation for hedge fund 1 and 8 at least up to lag 3, for hedge fund 4 at least up to lag 11, for hedge fund 7 at least up to lag 6 and for hedge fund 9 at least up to lag 2. Since the squared returns measures the second order moment of the original time series, these results indicate that the variance of the ten hedge funds conditional on their past history may change over time, or equivalently, the time series of the hedge funds may exhibit time varying conditional heteroskedasticity or volatility clustering.

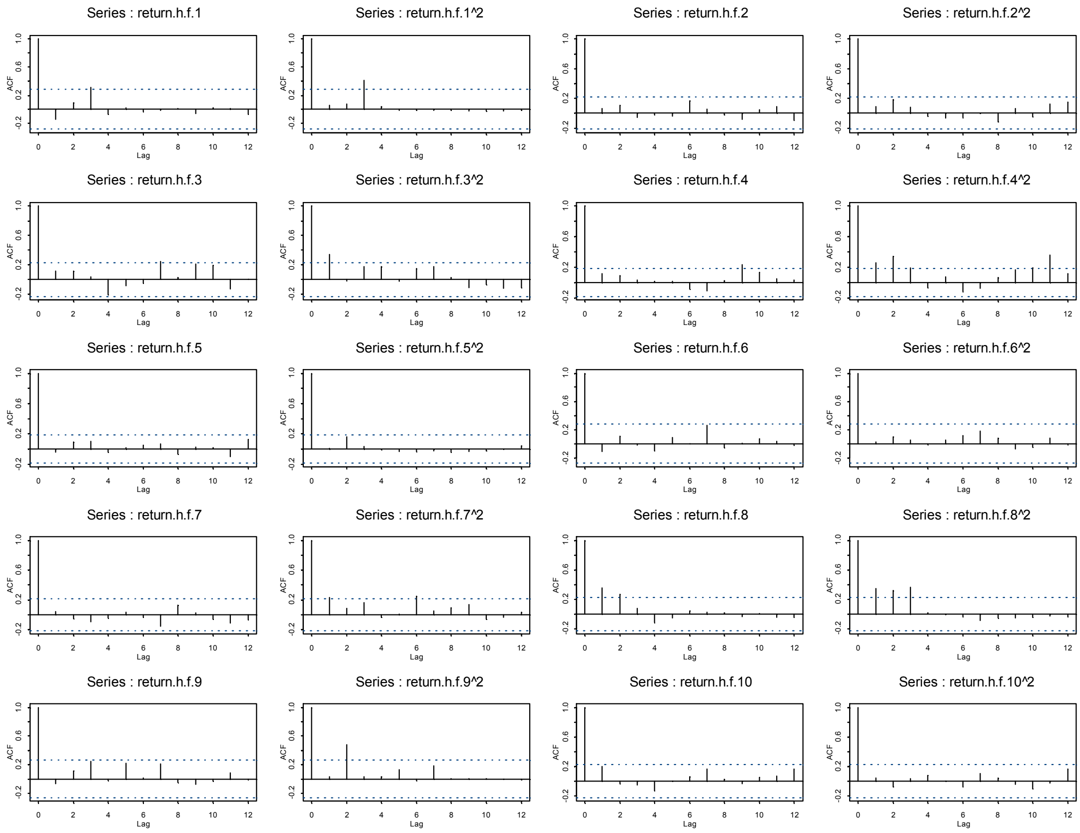


Figure 7.2: The autocorrelation plots of the monthly returns and squared monthly returns of the ten hedge funds.

7.3 Descriptive statistics

In each statistical research, the first step is constituted by the synopsis of the descriptive statistics of our data. We need this process to get a first sight on the behaviour and on the distribution of our data.

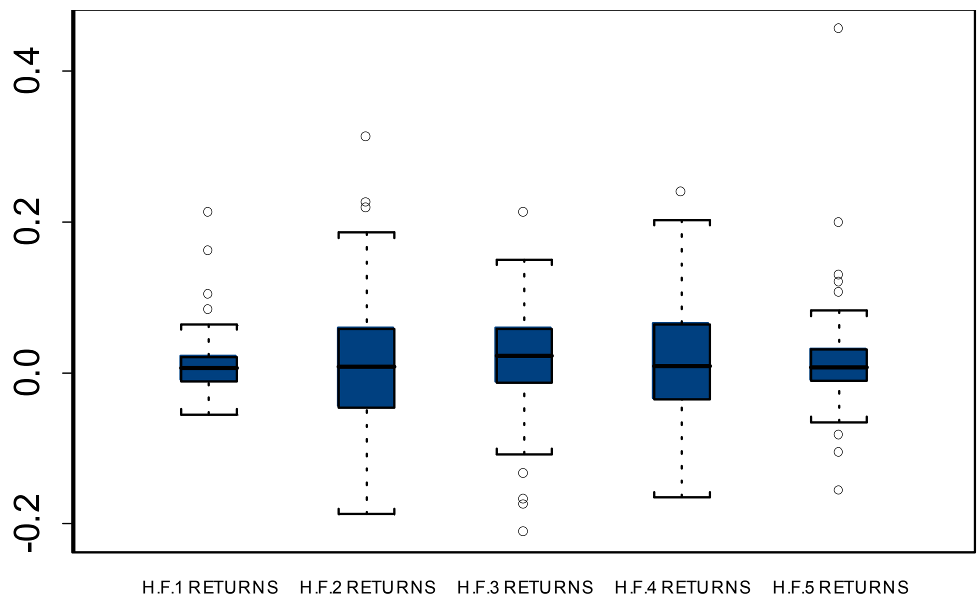
	MEAN	MEDIAN	ST.DEV	KURTOSIS	SKEWNESS	1^{ST} Q.	3^{RD} Q.	MIN	MAX
HF1	0.0138	0.0061	0.0469	7.273	2.312	-0.0113	0.021	-0.0555	0.2116
HF2	0.0102	0.0076	0.0941	0.5756	0.4598	-0.0455	0.0579	-0.1876	0.3116
HF3	0.0149	0.022	0.0715	1.8143	-0.7197	-0.013	0.058	-0.212	0.2119
HF4	0.016	0.0084	0.0762	0.3831	0.2416	-0.0357	0.064	-0.1654	0.2387
HF5	0.0137	0.0066	0.0624	3.2089	3.3345	-0.0108	0.031	-0.1572	0.4546
HF6	0.0188	0.013	0.045	0.1081	0.4119	-0.0039	0.0384	-0.0701	0.1391
HF7	0.007	0.0125	0.0483	0.3955	-0.0087	-0.0285	0.0379	-0.1142	0.1514
HF8	0.0156	0.0091	0.074	5.2291	1.7384	-0.0195	0.0392	-0.103	0.2969
HF9	0.0102	0.0022	0.037	8.9858	2.5204	-0.0054	0.0161	-0.0635	0.1723
HF10	0.0056	0.0114	0.0454	4.7745	-1.4472	-0.0109	0.0273	-0.1967	0.0945

Table 7.1: Summary statistics of the ten hedge funds.

We present the mean, median, standard deviation, kurtosis, skewness, first quantile, third quantile, minimum and maximum values of the series returns for the ten hedge funds.

When we observe the mean returns, we conclude that the series of the ten hedge funds are all positive. Hedge fund 6 has the highest mean (0.0188) and hedge fund 10 has the smallest one (0.0056). In regard to median, we observe that hedge fund 3 has the highest value of median (0.022) and hedge fund 9 has the smallest one (0.0022). The standard deviation gives a measure of risk. Hedge fund 2 presents the highest risk (0.0941) and hedge fund 9 presents the smallest risk (0.037). In regard to kurtosis, hedge fund 9 shows the highest value (8.9858) and hedge fund 6 (0.1081) shows the smallest one. Generally, a relatively big value of kurtosis is combined with phenomenon, which we try to capture using ARCH and GARCH models. Hedge fund 5 presents in an absolute value, the highest skewness (3.3345) and hedge fund 7 presents the smallest one (0.0087). When we examine the range of the series' values, we observe that there is a significant variability on these.

In the following, we present graphically the behaviour of the data via a boxplot in order to obtain a total picture of them.



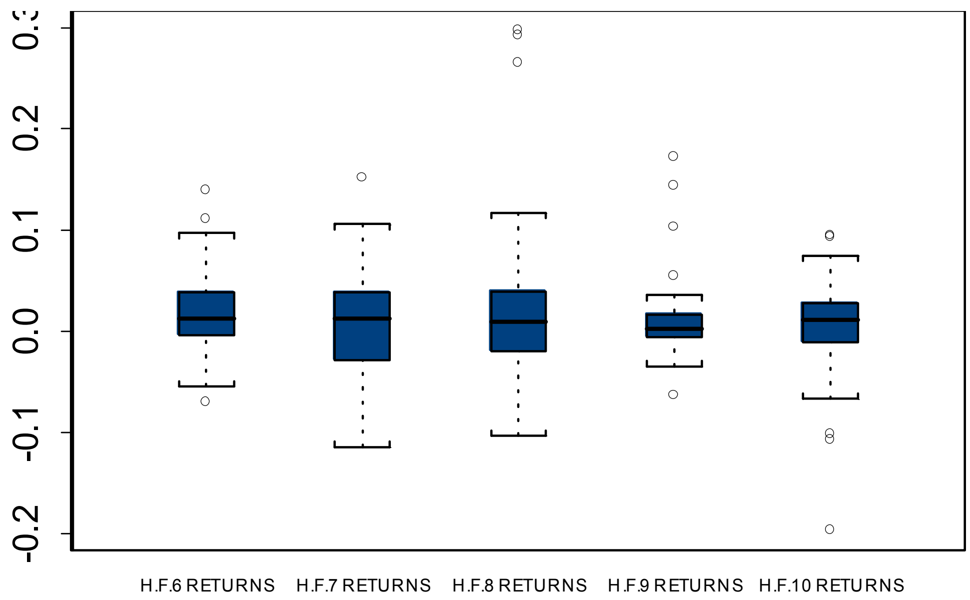


Figure 7.3: The boxplots for the monthly returns of all hedge funds.

7.4 Single factor model

We apply a single factor model with the following expression: $R_{it} = \alpha_{it} + \beta_{it} \times R_{RUS,t} + \varepsilon_{it}$ (7.1), where R_{it} is the return on the hedge fund i at time t, α_{it} is the abnormal performance of the hedge fund i at time t, β_{it} is the slope coefficient or the sensitivity of hedge fund i at time t, $R_{RUS,t}$ is the return on factor Russell 3000 equity index at time t and ε_{it} is the error term of the hedge fund i at time t. Specifically, we apply this model ten times for each hedge fund. In table 7.2, we receive the coefficients of alpha, beta, their respective p-values and the values of the adjusted R^2, in each case.

SINGLE FACTOR MODEL			
	ALPHA	**BETA**	**ADJ. R. SQ**
HF1	0,0161* (0,0112)	0,3969* (0,0014)	0,1802
HF2	0,0075 (0,3202)	1,3751* (0,00002)	0,4855
HF3	0,015* (0,049)	0,6075* (0,00003)	0,1971
HF4	0,015* (0,0345)	0,253 (0,1258)	0,0117
HF5	0,0136* (0,0264)	0,0212 (0,8683)	0,0091
HF6	0,0213* (0,0006)	0,4085* (0,0005)	0,2109
HF7	0,0067 (0,1997)	0,1744 (0,0869)	0,0236
HF8	0,0156 (0,056)	0,4712* (0,0032)	0,0992
HF9	0,0109* (0,0315)	0,1365 (0,1672)	0,0172
HF10	0,0056 (0,2452)	0,3384* (0,0005)	0,1414

Table 7.2: Coefficients of the single factor model.

The results of a single factor model of 10 hedge funds. In the brackets, there are the corresponding p-values of alphas, betas and the adjusted R-squared. With (*), we denote the quantities which are statistically significant at the 5% significance level.

Jensen (1968) was the first to systematically test the performance of mutual funds and in particular examine whether any "beats the market". The quantity of interest is the significance of a_i which is the intercept in the regression of the fund's excess returns on the excess returns of one or more passive benchmarks and is named Jensen's alpha, since this parameter defines whether the fund outperforms or underperforms the market index. This parameter also presents the manager's skill. In particular, alpha is a common measure to compare a manager's performance to a benchmark that represents the market in which the hedge fund participates. A positive and significant a_i for a given fund would suggest that the fund is able to earn significant abnormal returns in excess of the market required return for a fund of this given riskiness. Thus, hedge fund 6 that has the biggest value of alpha (0.0213), will produce a return that is 2.13% higher than the benchmark.

We apply t-tests in order to test the significance of the Jensen's alpha and beta coefficients. The null hypothesis of t-test asserts that the coefficient of the regression is equal to zero. Specifically, the null hypothesis refers that Jensen's alpha is equal to zero. We applied ten regressions, one of each hedge fund and we obtain the respective alphas and their p-values. Looking at table 7.2, we conclude that the alpha coefficients are statistically significant only in the cases of hedge fund 1, 3, 4, 5, 6 and 9 at the 5% significance level. Examining the performance of hedge funds, we can conclude that hedge fund 6 and 1 have values of alpha 0.0213 (p-value: 0.0006) and 0.161 (p-value: 0.0112) respectively, that means better performance in contrary to the rest hedge funds. In the following, we apply t-tests in order to test the significance of the beta coefficients. The null hypothesis asserts that the beta coefficient is equal to zero. From table 7.2, we conclude that the beta coefficients are statistically significant only in the cases of hedge fund 1, 2, 3, 6, 8 and 10 at the 5% significance level. We observe that the beta coefficients are relatively small which means that all hedge funds have low systematic risks.

We will discuss the third column of table 7.2, which presents the values of the adjusted R^2. Firstly, we will introduce a brief paragraph for the adjusted R^2. Some quantities known as goodness of fit statistics, which are available to test how well the sample regression function fits the data, play a crucial role to the statistical inference. The values of R^2 must lie between 0 and 1. If this value is high, the model fits the data well, while if this value is low (close to zero), the model does not provide a good fit to the data.

In table 7.2, we adduce the values of adjusted R^2 in contrary to the values of R^2, which are eliminated. R^2 is defined in terms of variation about the mean of y. It is not sensible to compare the value of R^2 across models with different dependent/independent variables. Furthermore, R^2 never falls if more regressors are added to the regression.

These reasons lead us to use only the values of the adjusted R^2 in order to overcome these problems. Specifically, the adjusted R^2 takes into account the loss of degrees of freedom associated with adding extra variables. It has the following type: $\text{adj.}R^2 = 1 - \left[\frac{T-1}{T-k-1}\left(1-R^2\right)\right]$, where T is the sample size and k is the number of the regressors. When k increases, then the adjusted R^2 will actually fall. In conclusion, adjusted R^2 can be used as a decision-making tool for determining whether a given variable should be included in a regression model or not.

The range for the values of adjusted R^2 is (0.0091,0.4855), which means that the excess returns of the market index is able to explain a relatively small proportion of the variability of the excess returns on the hedge funds. So, the above models appear to be rather poor for explaining the variability of the hedge funds returns.

ITEM	MEAN VALUE	MEDIAN VALUE	MINIMUM VALUE	MAXIMUM VALUE
$\hat{a}$	0.01273	0.0143	0.0056	0.0212
$\hat{b}$	0.41827	0.3677	0.0213	1.3751

Table 7.3: Summary statistics for the estimated regression results from the regression of 7.1.

In table 7.3, we present the mean, median, minimum and maximum values of the Jensen's alpha for the ten models. We observe that the average (defined as either the mean or median) hedge fund is able to 'beat the market', recording a positive alpha in both cases. The best hedge fund of all yields an alpha of 0.0212 (hedge fund 6).

Furthermore, we present the mean, median, minimum and maximum values for all beta coefficients and we summarize that the average fund has a beta estimate of around 0.42, indicating that, the single factor model, most funds were less risky than the market index. Hedge fund 2, which has the maximum value of 1.3751, is riskier than the market index. In this case we refer to Russell 3000 as market index.

RESIDUAL DIAGNOSTICS			
	JARQUE-BERA TEST	**LJUNG-BOX TEST (AUTOCORRELATION)**	**LJUNG-BOX TEST (HETEROSKEDASTICITY)**
HF1	78,6857* (0,0000)	9,9318 (0,8702)	7,4241 (0,9642)
HF2	81,2163* (0,0000)	20,5574 (0,3618)	18,854 (0,4662)
HF3	15,7279* (0,0004)	20,3031 (0,316)	23,9854 (0,1555)
HF4	4,862 (0,0879)	35,5606* (0,0173)	68,2092* (0,0000)
HF5	24,1875* (0,0000)	12,6726 (0,891)	5,9494 (0,999)
HF6	1,6283 (0,443)	14,0629 (0,594)	20,2973 (0,2071)
HF7	0,4632 (0,7933)	16,3978 (0,6306)	29,7291 (0,0553)
HF8	13,2679* (0,0000)	24,411 (0,142)	38,3574* (0,0035)
HF9	20,7132* (0,0000)	13,06 (0,7322)	17,3625 (0,4301)
HF10	17,9621* (0,0001)	20,6626 (0,2968)	17,3884 (0,4966)

Table 7.4: Residual diagnostics of the single factor model.

The Jarque-Bera and Ljung-Box statistics for the standardized residuals and squared standardized residuals as well as their p-values, which are in the brackets. With (*), we denote the quantities which are statistically significant at the 5% significance level.

In the following of this study (table 7.4), we apply two different tests for three different hypotheses. The first test is applied to check for normality of the residuals (Jarque-Bera test), and the second, to test for the existence of autocorrelation in the standardized residuals and for the presence of heteroskedasticity in the squared standardized residuals (Ljung-Box). The results from these tests are presented in the above table.

One of the most commonly applied tests for normality is the Jarque-Bera test. It tests whether the coefficient of skewness and the coefficient of excess kurtosis are jointly zero. The Jarque-Bera statistic is defined as follows: $W = T\left[\frac{b_1^2}{6} + \frac{(b_2 - 3)^2}{24}\right]$, where T is the sample size. If we denote the error by u and its variance by σ^2, it can be proved that the coefficients of skewness and kurtosis can be expressed respectively as, $b_1 = E(u^3)/(\sigma^2)^{3/2}$ and $b_2 = E(u^4)/(\sigma^2)^2$. The kurtosis of the normal distribution is 3 so its excess kurtosis $(b_2 - 3)$ is zero. b_1 and b_2 can be estimated using the residuals from the OLS regression, $\hat{u}$. The null hypothesis suggests normality and this would be rejected if the residuals of the model were either significantly skewed or leptokurtic/platykurtic, or both. The single factor model, we concluded that the normality, in the residual series, is rejected at the significance level of 5% in regard to hedge fund 1, 2, 3, 5, 8, 9 and 10, implying that the inferences we make about the coefficient estimates could be wrong.

In the following, we will apply Ljung-Box test at the standardized residuals in order to detect the existence of autocorrelation. Box and Pierce (1970) created the Q-statistic to check if the correlation coefficients are simultaneously equal to zero. But the results from the application of this test that lead to the wrong decision too frequently for small samples. This problem drove Ljung and Box (1978) to create a modified Q-statistic, which is known as the Ljung-Box statistic, as: $Q = T(T+2)\sum_{k=1}^{m} \hat{\tau}_k^2 / T-k \sim \chi_m^2$, where m is the maximum k lag length and $\hat{\tau}_k$ are the kth autocorrelation.

The null hypothesis of the Ljung-Box test, when we want to test for the existence of autocorrelation in standardized residuals, refers to no autocorrelation. The Ljung-Box Q-statistic for the standardized residuals series, suggests that there is no significant autocorrelation, except for one case. Specifically, we reject the null hypothesis (p-value: 0.0173) in the case of hedge fund 4.

The null hypothesis of the Ljung-Box test, when we want to test for the existence of heteroskedasticity between the standardized residuals, ie autocorrelation between the squared standardized residuals, refers to no heteroskedasticity. Looking at table 7.4, we conclude that there is no conditional heteroskedasticity in the squared standardized residuals apart from two cases. Specifically, we reject the null hypothesis (p-value: 0.00003, p-value: 0.0035), at the 5% of significance level, in the case of hedge funds 4 and 8, respectively. We assume that there is evidence of heteroskedasticity.

7.5 Fama and French three factor model

We apply the Fama and French three factor model, which has been well known for its explanatory power of mutual funds returns, with the following expression: $R_{it} = \alpha_i + \beta_{1,i} \times R_{RUS,t} + \beta_{2,i} \times R_{SMB,t} + \beta_{3,i} \times R_{HML,t} + \varepsilon_{it}$ (7.2), where R_{it} is the return on the hedge fund i at time t, α_i is the abnormal performance of the hedge fund i at time t, $\beta_{1,i}$, $\beta_{2,i}$ and $\beta_{3,i}$ are the beta coefficients of hedge fund i at time t, $R_{RUS,t}$ is the return on factor Russell 3000 equity index at time t, $R_{SMB,t}$ is the factor mimicking portfolio for size at time t, $R_{HML,t}$ is the factor mimicking portfolio for book-to-market equity at time t and ε_{it} is the error term of the hedge fund i at time t. We apply this model ten times for the returns of each hedge fund. In table 7.5, we receive the coefficients of alpha, beta, their respective p-values and the values of the adjusted R^2, in each case.

THREE FACTOR MODEL					
	ALPHA	**BETA1**	**BETA2**	**BETA3**	**ADJ. R. SQ**
HF1	0,021* (0,0019)	0,4109* (0,0008)	-0,1807 (0,2219)	-0,2677* (0,0169)	0,247
HF2	0,0035 (0,4836)	1,1988* (0,00002)	0,8635* (0,00004)	-0,4725* (0,00002)	0,7778
HF3	0,0118 (0,1231)	0,5853* (0,0001)	0,4022* (0,0354)	0,1827 (0,2404)	0,2272
HF4	0,0145* (0,032)	0,1377 (0,3829)	0,3955* (0,0407)	-0,3969* (0,0131)	0,1274
HF5	0,0137* (0,0099)	-0,1418 (0,2108)	0,452* (0,0018)	-0,468* (0,0001)	0,2592
HF6	0,017* (0,0063)	0,3475* (0,0022)	0,3262* (0,0208)	0,0106 (0,9167)	0,2864
HF7	0,0077 (0,1188)	0,2533* (0,0101)	-0,3284* (0,0087)	0,1671 (0,095)	0,1577
HF8	0,0147* (0,0159)	0,2551* (0,0309)	0,54* (0,0005)	-0,6456* (0,00003)	0,5218
HF9	0,01* (0,022)	0,0724 (0,3723)	0,1626 (0,1033)	-0,2945* (0,0002)	0,352
HF10	0,0032 (0,4778)	0,3272* (0,0004)	0,3894* (0,001)	0,2328* (0,0099)	0,2629

Table 7.5: Coefficients of the three factor model.

In the brackets, there are the corresponding p-values of alphas, betas and the adjusted R-squared. With (*), we denote the quantities which are statistically significant at the 5% significance level.

We apply t-tests in order to test the significance of the alpha coefficients, which have arisen from the application of the above ten regressions with the general form (7.2). The null hypothesis refers that alpha coefficient is equal to zero. Studying the results from table 7.5, we conclude that the alpha coefficients are statistically significant only in the cases of hedge fund 1, 4, 5, 6, 8 and 9 at the 5% significance level. This means that these hedge funds are able to earn significant abnormal returns. The most profitable hedge funds are 1 and 6 with values of alpha 0.021 (p-value: 0.0019) and 0.017 (p-value: 0.0063), respectively. As a result, we are able to comprehend hedge fund 1 and 6 in our portfolio. We conclude that hedge fund 1 will produce a return that is 2.1% higher than the benchmarks and hedge fund 2 will produce a return that is 1.7% higher than the benchmarks.

We, also, apply t-tests in order to test the significance of the beta coefficients. The null hypothesis maintains that the beta coefficient is equal to zero. From table 7.5, we conclude that the beta coefficients for the Russell 3000 equity index are statistically significant only in the cases of hedge fund 1, 2, 3, 6, 7, 8 and 10 at the significance level of 5%. In regard to beta coefficients on the factor mimicking portfolio for size, we conclude that the null hypothesis is rejected at the cases of hedge fund 2, 3, 4, 5, 6, 7, 8 and 10 at the 5% significance level. The beta coefficients of the factor mimicking portfolio for book-to-market equity are statistically significant in the cases of hedge fund 1, 2, 4, 5, 8, 9 and 10. Specifically, hedge fund 1, 2, 3, 6, 7, 8 and 10 load significantly positive on the factor Russell 3000 equity index (RUS) at the 5% significance level. Hedge fund 2, 3, 4, 5, 6, 8 and 10 load significantly positive on the factor mimicking portfolio for size (SMB) and hedge fund 7 loads significantly negative on the same factor at the 5% significance level. Hedge fund 10 loads significantly positive on the factor mimicking portfolio for book-to-market equity (HML) and hedge fund 1, 2, 4, 5, 8 and 9 load significantly negative on the same factor at the 5% significance level.

We will discuss the sixth column of the table which presents the values of the adjusted R^2. The range for the values of adjusted R^2 is (0.1274, 0.7778), which means that the excess returns of the three factors are able to explain a relative small proportion of the variability of the excess returns on the hedge funds. The average adjusted R^2 improves considerably to 0.322 compared to 0.136 from the single factor model.

ITEM	MEAN	MEDIAN	MINIMUM	MAXIMUM
$\hat{\alpha}$	0,01171	0,01275	0,0032	0,021
$\hat{\beta}_1$	0,34464	0,29115	-0,1418	1,1988
$\hat{\beta}_2$	0,30223	0,39245	-0,3284	0,8635
$\hat{\beta}_3$	-0,1952	-0,2811	-0,6456	0,2328

Table 7.6: Summary statistics for the estimated regression results from the regression of 7.2.

In table 7.6, we present the mean, median, minimum and maximum values of the alphas' coefficients for the ten models. We observe that the average (defined as either the mean or median) hedge fund means that there is a positive manager's skill, recording positive alpha in both cases. The best hedge fund of all yields an alpha of 0.021.

Furthermore, we present the mean, median, minimum and maximum values of all beta coefficients for the three market indices. The mean for all beta coefficients are relatively small, conclusion that indicates that most hedge funds are less risky than the market indices.

RESIDUAL DIAGNOSTICS			
	JARQUE-BERA TEST	LJUNG-BOX TEST (AUTOCORRELATION)	LJUNG-BOX TEST (HETEROSKEDASTICITY)
HF1	27,8054* (0,00002)	11,5791 (0,7724)	11,4388 (0,7816)
HF2	0,2648 (0,876)	19,8307 (0,4048)	19,5474 (0,4223)
HF3	14,2872* (0,0008)	11,9969 (0,8474)	21,2779 (0,2656)
HF4	15,1549* (0,0005)	22,5927 (0,3092)	49,3197* (0,0003)
HF5	253,6525* (0,00001)	18,1216 (0,5794)	26,9624 (0,1363)
HF6	0,6104 (0,737)	13,0542 (0,6688)	18,5419 (0,2931)
HF7	0,6194 (0,7337)	13,2282 (0,8267)	14,4069 (0,7595)
HF8	5,0407 (0,0804)	21,5593 (0,2521)	18,3098 (0,4354)
HF9	21,5061* (0,00002)	18,5597 (0,3544)	25,6975 (0,0802)
HF10	18,1858* (0,0001)	8,4816 (0,9706)	18,0816 (0,4503)

Table 7.7: Residual diagnostics of the three factor model.

The Jarque-Bera and the Ljung-Box statistics for the standardized residuals and squared standardized residuals as well as their p-values, which are in the brackets. With (*), we denote the quantities which are statistically significant at the 5% significance level.

In the following, we proceed to test the significance of the null hypothesis, which refers that there is normality in the residuals series.

Purposely, we apply the Jarque-Bera test and we conclude that the null hypothesis of normality is rejected in the cases of hedge fund 1, 3, 4, 5, 9 and 10 at the 5% significance level, implying that the inferences we make about the coefficient estimates could be wrong.

Afterwards, we apply the Ljung-Box test in order to test the existence of autocorrelation in the standardized residuals series. The null hypothesis asserts that there is no autocorrelation. The Ljung-Box Q-statistic for the standardized residuals series after fitting the three factor model of Fama and French, suggests that there is no autocorrelation problem.

We accomplish with the application of the Ljung-Box test on the squared standardized residuals series in order to test if there is evidence of heteroskedasticity in the standardized residuals. Thus, the null hypothesis refers to no heteroskedasticity in the standardized residuals. Looking at table 7.7, we reject the null hypothesis for hedge fund 4, which has value of Ljung-Box statistic 49.32 (p-value: 0.0003).

7.6 Carhart four factor model

We will apply the four factor model of Carhart (1997), which is an extension of the Fama and French (1993) three factor model. It takes into account size and book-to-market ratio, but also an additional factor for the momentum effect. The applied four factor model is the following: $R_{it} = \alpha_i + \beta_{1,i} \times R_{RUS,t} + \beta_{2,i} \times R_{SMB,t} + \beta_{3,i} \times R_{HML,t} + \beta_{4,i} \times R_{MOM,t} + \varepsilon_{it}$ (7.3), where R_{it} is the return on the hedge fund i at time t, α_i is the abnormal performance of the hedge fund i at time t, $\beta_{1,i}$, $\beta_{2,i}$, $\beta_{3,i}$ and $\beta_{4,i}$ are the beta coefficients of hedge fund i at time t, $R_{RUS,t}$ is the return on factor Russell 3000 equity index at time t, $R_{SMB,t}$ is the factor mimicking portfolio for size at time t, $R_{HML,t}$ is the factor mimicking portfolio for book-to-market equity at time t, $R_{MOM,t}$ is the momentum factor at time t and ε_{it} is the error term of the hedge fund i at time t. We apply this model ten times for the returns of each hedge fund. In table 7.8, we receive the coefficients of alpha, beta, their respective p-values and the values of the adjusted R^2, in each case.

FOUR FACTOR MODEL						
	ALPHA	**BETA1**	**BETA2**	**BETA3**	**BETA4**	**ADJ. R. SQ**
HF1	0,0206* (0,0042)	0,4225* (0,0048)	-0,1681 (0,3351)	-0,2495 (0,1464)	0,0137 (0,8881)	0,2302
HF2	0,0092 (0,0514)	0,9317* (0,00002)	0,6048* (0,0003)	-0,8615* (0,0003)	-0,3423* (0,0006)	0,8221
HF3	0,0052 (0,4984)	0,8229* (0,00004)	0,6615* (0,002)	0,577* (0,008)	0,3189* (0,0109)	0,2876
HF4	0,0084 (0,2143)	0,4167* (0,019)	0,695* (0,0011)	0,0442 (0,8302)	0,3936* (0,002)	0,192
HF5	0,0106 (0,0502)	-0,0026 (0,984)	0,5946* (0,0002)	-0,245 (0,1254)	0,199* (0,042)	0,2814
HF6	0,0219* (0,0007)	0,1714 (0,1759)	0,1351 (0,3764)	-0,2647 (0,0803)	-0,2073* (0,0187)	0,3572
HF7	0,0055 (0,2717)	0,3615* (0,0018)	-0,2169 (0,113)	0,3382* (0,015)	0,15 (0,075)	0,1808
HF8	0,013* (0,0353)	0,3451* (0,0137)	0,6308* (0,0003)	-0,5047* (0,0026)	0,1226 (0,2202)	0,5252
HF9	0,0112* (0,0152)	0,0204 (0,8385)	0,1091 (0,3483)	-0,3725* (0,002)	-0,0612 (0,379)	0,3493
HF10	0,0011 (0,8018)	0,4407* (0,0001)	0,5039* (0,0001)	0,4104* (0,0011)	0,1547* (0,0401)	0,2958

Table 7.8: Coefficients of the four factor model.

The results of a single factor model of 10 hedge funds. In the brackets, there are the corresponding p-values of alphas, betas and the adjusted R-squared. With (*), we denote the quantities which are statistically significant at the 5% significance level.

We apply t-tests in order to test the significance of the alpha coefficients, which have arisen from the application of the above ten regressions with the general form (7.3). The null hypothesis refers that alpha coefficient is equal to zero. Looking at table 7.8, we conclude that the coefficients of alpha are all positive, which means that it provides some evidence that this sample of hedge fund managers do have superior relative performance by means of asset selections. We also summarize that the alpha coefficients are statistically significant only in the cases of hedge fund 1, 6, 8 and 9, at the 5% significance level. Hedge fund 6 seems to perform the best with alpha's value 0.0219 (p-value: 0.0007), followed by hedge fund 1 with value of alpha 0.0206 (p-value: 0.0042). Accordingly, we are able to comprehend hedge fund 1 and 6 in our portfolio. As we observe until now, the four factor model of Carhart gives hedge fund 1 and 6 as the most profitable hedge funds. It is remarkable to refer that the single factor model as the three factor model of Fama and French conclude to the same results with the four factor model of Carhart, in regard to the best performing hedge funds.

We also apply t-tests in order to test the significance of the beta coefficients. The null hypothesis maintains that the beta coefficient is equal to zero. Hedge fund 1, 2, 3, 4, 7, 8 and 10 load significantly positive on the factor Russell 3000 equity index at the 5% significance level. Hedge fund 2, 3, 4, 5, 8 and 10 load significantly positive on the factor mimicking portfolio for size (SMB) at the 5% significance level. Hedge fund 3, 7 and 10 load significantly positive on the factor mimicking portfolio for book-to-market equity (HML) and hedge fund 2, 8 and 9 load significantly negative on the same factor at the 5% significance level. Hedge fund 3, 4, 5 and 10 load significantly positive on the momentum factor (MOM) and hedge fund 2 and 6 load significantly negative on the same factor at the 5% significance level.

The range for the values of the adjusted R^2 is (0.1808, 0.8221), which means that the four factors are able to explain a relatively small proportion of the variability of the excess returns on the hedge funds, except the returns of hedge fund 2. The average adjusted R^2, barely, improves to 0.352 compared to 0.322 from the three factor of Fama and French.

ITEM	MEAN	MEDIAN	MINIMUM	MAXIMUM
$\hat{a}$	0,01067	0,0099	0,0011	0,0219
$\hat{b}_1$	0,39303	0,3891	-0,0026	0,695
$\hat{b}_2$	0,35498	0,54925	-0,2169	0,577
$\hat{b}_3$	-0,11281	-0,24725	-0,8615	0,577
$\hat{b}_4$	0,07417	0,1363	-0,3423	0,3936

Table 7.9: Summary statistics for the estimated regression results from the regression of 7.2.

In table 7.9, we present the mean, median, minimum and maximum values of the alphas coefficients for the ten models. We observe that the average (defined as either the mean or median) hedge fund means that there is a positive manager's skill, recording positive alpha in both cases. The best hedge fund of all yields an alpha of 0.577.

Furthermore, we present the mean, median, minimum and maximum values of all beta coefficients for the ten models. The average beta coefficients are relatively small, conclusion that indicates that most hedge funds are less risky than the market indices.

RESIDUAL DIAGNOSTICS			
	JARQUE-BERA TEST	**LJUNG-BOX TEST (AUTOCORRELATION)**	**LJUNG-BOX TEST (HETEROSKEDASTICITY)**
HF1	28,1526* (0,0000)	11,8296 (0,7556)	11,5482 (0,7745)
HF2	1,0486 (0,592)	11,4014 (0,9096)	17,5278 (0,5542)
HF3	5,142 (0,0765)	13,9099 (0,7349)	26,1684 (0,096)
HF4	29,4401* (0,0000)	38,085* (0,0086)	22,9107 (0,2932)
HF5	281,7345* (0,0000)	17,3163 (0,6323)	23,2958 (0,2745)
HF6	0,2652 (0,8758)	12,9151 (0,679)	12,4231 (0,7144)
HF7	0,6914 (0,7077)	14,3679 (0,7618)	15,8792 (0,6653)
HF8	6,0215* (0,0493)	24,1882 (0,149)	19,6744 (0,3514)
HF9	18,2773* (0,0001)	20,9632 (0,2279)	24,7692 (0,1)
HF10	10,7832* (0,0046)	9,0521 (0,9585)	18,625 (0,4152)

Table 7.10: Residual diagnostics of the four factor model.

The Jarque-Bera and Ljung-Box statistics for the standardized residuals and squared standardized residuals as well as their p-values, which are in the brackets. With (*), we denote the quantities, which are statistically significant at the 5% significance level.

In the following, we proceed to test the significance of the null hypothesis of the Jarque-Bera test, which refers that there is normality at the residuals series. Specifically, we apply this test and we conclude that the null hypothesis of normality is rejected in the cases of hedge fund 1, 4, 5, 8, 9 and 10 at the 5% significance level, implying that the inferences we make about the coefficient estimates could be wrong.

Afterwards, we apply the Ljung-Box test in order to test the existence of autocorrelation in the standardized residuals series. The null hypothesis asserts that there is no autocorrelation. The Ljung-Box Q-statistic for the standardized residuals series after fitting the four factor model of Carhart, suggests that the null hypothesis is rejected only in the case of hedge fund 4 (38.085, p-value: 0,0086).

We accomplish with the application of the Ljung-Box test on the squared standardized residuals series in order to test the evidence of heteroskedasticity in the standardized residuals. The null hypothesis refers to no heteroskedasticity in the squared standardized residuals. Looking at table 7.10, we conclude that there is no heteroskedasticity in the squared standardized residuals series.

7.7 Multi-factor model

Many market indices can be used to evaluate hedge funds. In our case we have 14 pricing factors that can be used in our models. Our aim is to detect the suitable set of market indices, which we lead us to safe conclusions relative to the evaluation of performance of hedge funds. This problem is usually referred to as model uncertainty. Until now, we have applied a single factor model, the three factor model of Fama and French and the four factor model of Carhart. It is necessary to use a backward procedure to identify significant hedge fund pricing factors in order to apply suitable models.

Our model has the following general expression: $R_{it} = \alpha_i + \sum_{k=1}^{K} \beta_k F_{kt} + \varepsilon_{it}$ (7.4), where R_{it} is the return of a hedge fund investment at time t, α_i is the abnormal performance of the hedge fund i at time t which is an aggregate measure of performance, β_k is the loading of risk factor k associated with the hedge fund, F_{kt} is the excess return of factor k at time t and ε_{it} is the error term of hedge fund i at time t.

In the regression, we use as independent variables the 14 market indices. We apply this regression ten times for each hedge fund, using the backward procedure to obtain the suitable factors in each case. In the following, we construct a table where its first column contains the brief names of the 14 market indices, which we comprehend in the regressions; so, the information variables are: the Russell 3000 equity index excess return (RUS), the Russell 3000 equity index excess return lagged once [RUS(-1)], the Morgan Stanley Capital International world excluding USA index excess return (MXUS), the Morgan Stanley Capital International emerging markets index excess return (MEM), Fama and French's (1993) 'size' (SMB) and 'book-to-market' (HML) as well as Carhart's (1997) 'momentum' factors (MOM), the Salomon Brothers world government and corporate bond index excess return (SBGC), the Salomon Brothers world government bond index excess return (SBWG), the Lehman high yield index excess return (LHY), the difference between the yield on the BAA-rated corporate bonds and the 10-year Treasury bonds (DEFSPR), the Goldman Sachs commodity index excess returns (GSCI), the Federal Reserve Bank competitiveness weighted dollar-index excess return (FRBI) and the change in S&P 500 implied volatility index (VIX).

Below, we show the regressions which arisen after the backward selection approach for each hedge fund.

Hedge fund 1:

$$R_{it} = \alpha_{it} + \beta_{1,i} XR_{RUS1,t} + \beta_{2,i} XR_{MEM,t} + \beta_{3,i} XR_{SMB,t} + \beta_{4,i} XR_{HML,t} + \beta_{5,i} XR_{DEFSPR,t} + \varepsilon_{it}$$

Hedge fund 2:

$$R_{it} = \alpha_{it} + \beta_{1,i} XR_{RUS,t} + \beta_{2,i} XR_{SMB,t} + \beta_{3,i} XR_{HML,t} + \beta_{4,i} XR_{MOM,t} + \varepsilon_{it}$$

Hedge fund 3:

$$R_{it} = \alpha_{it} + \beta_{1,i} XR_{MEM,t} + \beta_{2,i} XR_{HML,t} + \beta_{3,i} XR_{MOM,t} + \varepsilon_{it}$$

Hedge fund 4:

$$R_{it} = \alpha_{it} + \beta_{1,i} XR_{MXUS,t} + \beta_{2,i} XR_{SMB,t} + \beta_{3,i} XR_{MOM,t} + \varepsilon_{it}$$

Hedge fund 5:

$$R_{it} = \alpha_{it} + \beta_{1,i} XR_{MXUS,t} + \beta_{2,i} XR_{SMB,t} + \beta_{3,i} XR_{MOM,t} + +\beta_{4,i} XR_{SBWG,t} + \beta_{5,i} XR_{DEFSPR,t} + \beta_{6,i} XR_{VIX,t} + \varepsilon_{it}$$

Hedge fund 6:

$$R_{it} = \alpha_{it} + \beta_{1,i} XR_{HML,t} + \beta_{2,i} XR_{MOM,t} + \varepsilon_{it}$$

Hedge fund 7:

$$R_{it} = \alpha_{it} + \beta_{1,i} XR_{RUS1,t} + \beta_{2,i} XR_{MEM,t} + \beta_{3,i} XR_{SMB,t} + \beta_{4,i} XR_{SBGC,t} + \beta_{5,i} XR_{DEFSPR,t} + \varepsilon_{it}$$

Hedge fund 8:

$$R_{it} = \alpha_{it} + \beta_{1,i} XR_{RUS,t} + \beta_{2,i} XR_{RUS1,t} + \beta_{3,i} XR_{SMB,t} + \beta_{4,i} XR_{HML,t} + \varepsilon_{it}$$

Hedge fund 9:

$$R_{it} = \alpha_{it} + \beta_{1,i} XR_{RUS,t} + \beta_{2,i} XR_{MXUS,t} + \beta_{3,i} XR_{HML,t} + \beta_{4,i} XR_{MOM,t} + \beta_{5,i} XR_{FRBI,t} + \varepsilon_{it}$$

Hedge fund 10:

$$R_{it} = \alpha_{it} + \beta_{1,i} XR_{SMB,t} + \beta_{2,i} XR_{HML,t} + \beta_{3,i} XR_{VIX,t} + \varepsilon_{it} .$$

In table 7.11, we receive the coefficients of alpha, beta, their respective p-values and the values of the adjusted R^2, in each case.

MULTIFACTOR MODEL										
	HF1	**HF2**	**HF3**	**HF4**	**HF5**	**HF6**	**HF7**	**HF8**	**HF9**	**HF10**
Alpha	0.0248* (0.0002)	0.0092 (0.0514)	0.0169* (0.0118)	0.0111 (0.0842)	0.0104* (0.0409)	0.0243* (0.0000)	0.0067 (0.1275)	0.0160* (0.0058)	0.0163* (0.0001)	0.0030 (0.4994)
RUS	-	0.9317 (0.0000)	-	-	-	-	-	0.2446 (0.0284)	-0.4433 (0.0079)	-
RUS1	0.2991 (0.0281)	-	-	-	-	-	0.3975 (0.0000)	0.3552 (0.0023)	-	-
MXUS	-	-	-	0.4197 (0.0061)	0.3546 (0.0188)	-	-	-	0.5406 (0.0013)	-
MEM	0.4786 (0.0000)	-	0.6807 (0.0000)	-	-	-	0.2675 (0.0000)	-	-	-
SMB	-0.3965 (0.0206)	0.6048 (0.0000)	-	0.6097 (0.0006)	0.7799 (0.0000)	-	-0.4886 (0.0000)	0.4188 (0.0052)	-	0.3671 (0.0014)
HML	-0.4044 (0.0008)	-0.8615 (0.0000)	0.3248 (0.0397)	-	-	-0.4105 (0.0002)	-	-0.7471 (0.0000)	-0.4196 (0.0000)	0.2122 (0.0149)
MOM	-	-0.3423 (0.0000)	0.2344 (0.0169)	0.3419 (0.0002)	0.2906 (0.0000)	-0.3003 (0.0000)	-	-	-0.1191 (0.0305)	-
SBGC	-	-	-	-	-	-	0.8349 (0.0203)	-	-	-
SBWG	-	-	-	-	-0.8295 (0.0045)	-	-	-	-	-
LHY		-	-	-	-	-	-	-	-	-
DEFSPR	10.3632 (0.0341)	-	-	-	8.6873 (0.0452)	-	10.3953 (0.0038)	-	-	-
FRBI	-	-	-	-	-	-	-	-	0.9158 (0.0267)	-
GSCI	-	-	-	-	-	-	-	-	-	-
VIX	-	-	-	-	0.3232 (0.0412)	-	-	-	-	-0.4008 (0.0001)
ADJ. R. SQ	0.3523	0.8221	0.4178	0.2068	0.3240	0.3521	0.3635	0.5747	0.4679	0.2993

Table 7.11: Coefficients of the multi-factor model.

The results of the applied multifactor models that have arisen by the backward procedure, of the hedge funds. In the brackets, there are the corresponding p-values of alphas, betas and the adjusted R-squared. With (*), we denote the quantities that are statistically significant at the 5% significance level (in regard to the alpha coefficients). All beta coefficients, which we present in the table, are statistically significant at the 5% significance level.

We apply t-tests in order to test the significance of the alpha coefficients, which have arisen from the application of the above ten regressions with the original form (7.4). The null hypothesis asserts that the alpha coefficient is equal to zero. Looking at table 7.11, we summarize that the alpha coefficients are statistically significant only in the cases of hedge fund 1, 3, 5, 6, 8 and 9 at the 5% significance level. Examining the performance of hedge funds, we can conclude that hedge fund 1 and 6 have values of alpha 0.0248 (p-value: 0.0002) and 0.0243 (p-value: 0.0000), respectively, that means better performance in contrary to the rest hedge funds. Accordingly, we are able to comprehend hedge fund 1 and 6 in our portfolio.

We also apply t-tests in order to test the significance of the beta coefficients. The null hypothesis asserts that the beta coefficient is equal to zero. Looking at table 7.11, we observe that hedge fund 2 and 8 load significantly positive on the factor Russell 3000 equity index and hedge fund 9 loads significantly negative on this factor at the 5% significance level. Hedge fund 1, 7 and 8 load significantly positive on the factor Russell 3000 equity index excess return lagged once [RUS(-1)] at the 5% significance level. Hedge fund 4, 5 and 9 load significantly on the factor Morgan Stanley Capital International world excluding USA index excess return (MXUS) at the 5% significance level. Hedge fund 1, 3 and 7 load significantly positive on the factor Morgan Stanley Capital International emerging markets index excess return (MEM) at the 5% significance level. Hedge fund 2, 4, 5, 8 and 10 load significantly positive on the factor mimicking portfolio for size and hedge fund 1 and 7 load significantly negative on the same factor at the 5% significance level. Hedge fund 3 and 10 load significantly positive on the factor mimicking portfolio for book-to-market equity and hedge fund 1, 2, 6, 8 and 9 load significantly negative on the same factor at the 5% significance level. Hedge fund 3, 4, 5 and 6 load significantly positive on the momentum factor and hedge fund 2 and 9 load significantly negative on the same factor at the 5% significance level. Hedge fund 7 loads significantly positive on the Salomon Brothers world government and corporate bond index excess return (SBGC) at the 5% significance level. Hedge fund 5 loads significantly negative on the Salomon Brothers world government bond index excess return (SBWG). Hedge fund 1, 5 and 7 load significantly positive on the difference between the yield on the BAA-rated corporate bonds and the 10-year Treasury bonds (DEFSPR) at the 5% significance level. Hedge fund 9 loads significantly positive on the Goldman Sachs commodity index excess returns (GSCI) at the 5% significance level. Hedge fund 5 loads significantly positive on the the change in S&P 500 implied volatility index (VIX) and hedge fund 10 loads significantly negative on the same factor at the 5% significance level.

The range for the values of the adjusted R^2 is (0.2068, 0.8221), which means that the factors are able to explain a relative small proportion of the variability of the excess returns on the hedge funds, except the returns of hedge fund 2. The average adjusted R^2, barely, improves to 0.4154 compared to 0.352 from the four factor model of Carhart.

RESIDUAL DIAGNOSTICS			
	JARQUE-BERA TEST	LJUNG-BOX TEST (AUTOCORRELATION)	LJUNG-BOX TEST (HETEROSKEDASTICITY)
HF1	7.4030* (0.0247)	14.6712 (0.5488)	9.0270 (0.9123)
HF2	1.0519 (0.5910)	11.3923 (0.9099)	17.5372 (0.5535)
HF3	3.9050 (0.1419)	14.9752 (0.6637)	19.7242 (0.3486)
HF4	17.0066* (0.0002)	36.5353* (0.0133)	27.5909 (0.1194)
HF5	28.761* (0.0000)	15.5531 (0.7439)	21.5200 (0.3671)
HF6	0.4698 (0.7906)	12.2807 (0.7244)	11.9765 (0.7456)
HF7	0.6433 (0.7250)	17.2907 (0.5702)	17.3823 (0.5640)
HF8	1.8703 (0.3925)	16.2774 (0.5732)	13.9667 (0.7313)
HF9	37.444 (0.1538)	18.9594 (0.3309)	12.0725 (0.7957)
HF10	9.99* (0.0068)	8.3524 (0.9729)	34.4612* (0.0110)

Table 7.12: Residual diagnostics of the multi-factor model.

The Jarque-Bera test and Ljung-Box statistics for the standardized and squared standardized residuals as well as their p-values, which are in the brackets. With (*), we denote the quantities which are statistically significant at the 5% significance level.

In the following (table 7.12), we proceed to test null hypothesis of the Jarque-Bera test, which refers that there is normality in the residuals series. Specifically, we apply this test and we conclude that the null hypothesis of normality is rejected in the cases of hedge fund 1, 4, 5 and 10 at the 5% significance level, implying that the inferences we make about the coefficient estimates could be wrong.

Afterwards, we apply the Ljung-Box test in order to test the existence of autocorrelation in the standardized residuals series. The null hypothesis asserts that there is no autocorrelation. The Ljung-Box Q-statistic for the standardized residuals series after fitting the multi-factor model, which has arisen by the backward process, suggests that there is no autocorrelation, apart from hedge fund 4 (36.5353) (p-value: 0.0133).

We accomplish with the application of the Ljung-Box test on the squared standardized residuals series in order to detect heteroskedasticity in the standardized residuals. So, the null hypothesis refers to no heteroskedasticity in the standardized residuals. Looking at table 7.12, we reject the null hypothesis for hedge fund 10, which has value of 34.4612 (p-value: 0.011).

7.8 Single factor GARCH model

As we have previously referred, the autocorrelation in the squared returns, or conditional heteroskedasticity can be modeled using a generalized autoregressive GARCH model for the squared residuals. For this reason, we proceed to the application of a single factor GARCH(1,1) model, with conditional mean equation such as: $R_{it} = \alpha_{i,t} + \beta_{i,t} \times R_{RUS,t} + \varepsilon_{it}$ (7.5), where R_{it} is the return on hedge fund i at time t, $\alpha_{i,t}$ is the abnormal performance of the hedge fund i at time t, $\beta_{i,t}$ is the slope coefficient or the sensitivity of hedge fund i at time t, $R_{RUS,t}$ is the return on the Russell 3000 equity index at time t and ε_{it} is the error term of the hedge fund i at time t. The conditional variance equation is $\sigma_t^2 = a_0 + a_1\varepsilon_{t-1}^2 + b_1\sigma_{t-1}^2$ (7.6), where a_0 (A in the table) denotes the constant in the conditional variance equation, a_1 denotes the estimated ARCH(1) parameter and b_1 denotes the estimated GARCH(1) parameter. Specifically, we apply this model ten times, once for each hedge fund. In table 7.13, we obtain the coefficients of alpha, beta, a_0, a_1 and b_1, as well as their p-values, in each case.

SINGLE FACTOR GARCH(1,1) MODEL					
	ALPHA	**BETA**	**A**	**ARCH(1)**	**GARCH(1)**
HF1	0,0056* (0,0001)	0,1633* (0,0000)	-0,0000007 (0,4924)	2,7648* (0,0005)	0,0551 (0,1655)
HF2	0,0003 (0,4805)	1,3322* (0,0000)	0,0008 (0,0652)	0,3429 (0,0653)	0,5048* (0,0173)
HF3	0,0188* (0,0078)	0,5425* (0,0006)	0,0051* (0,0000)	0,1769 (0,0976)	-0,5596* (0,0247)
HF4	0,0087 (0,0891)	0,5961* (0,0000)	0,0011 (0,1006)	0,2961* (0,0151)	0,5126* (0,015)
HF5	0,0046 (0,057)	0,0095 (0,4478)	0,0003* (0,0092)	0,9476* (0,001)	0,2895* (0,0016)
HF6	0,019* (0,0011)	0,3899* (0,0001)	-0,0001 (0,22)	-0,0078 (0,4732)	1,0292* (0,0000)
HF7	0,0084* (0,0393)	0,2155* (0,003)	0,0002 (0,2289)	0,3259 (0,0793)	0,6231* (0,0012)
HF8	0,0056 (0,1623)	0,3373* (0,0003)	0,0009* (0,0083)	0,7846* (0,0007)	0,1847 (0,09)
HF9	-0,0004 (0,4127)	0,1044* (0,0031)	0.00005* (0,0425)	1,1146* (0,0004)	0,2492* (0,0065)
HF10	0,0058 (0,1405)	0,2814* (0,0045)	0,0002 (0,0508)	0,4222* (0,0045)	0,5391* (0,0000)

Table 7.13: Coefficients of the single factor GARCH(1,1) model.

In the brackets, there are the corresponding p-values of alphas, betas, a_0, a_1 and b_1. With (*), we denote the quantities which are statistically significant at the 5% significance level.

The quantity of interest is the significance of alphas ($\alpha_{i,t}$) which are the intercepts in the regressions of the fund's excess returns on the excess returns of Russell 3000 equity index. We apply t-tests in order to ensure the significance of the alpha coefficients. Specifically, the null hypothesis refers that the alpha coefficient is equal to zero. Looking at table 7.13, we conclude that hedge fund 1, 3, 6 and 7 are statistically significant at the 5% significance level. Hedge fund 6 seems to perform the best, because it has alpha equal to 0.019 (p-value: 0.0011), followed by hedge fund 3, which has value of alpha equal to 0.0188 (p-value: 0.0078). Consequently, we can get these hedge funds to our portfolio.

In the following, we observe of the beta coefficients, which are all positive apart from hedge fund 5 and all hedge funds load significantly on the Russell 3000 equity index. We end to this assumption because we apply t-tests, at which the null hypothesis refers that the beta coefficient is equal to zero (this hypothesis is rejected for all hedge funds at the 5% significance level). In the same way, we conclude that the a_0's, the a_1's and the b_1's, are statistically significant in the cases of hedge fund 3, 5, 8 and 9, are statistically significant in the cases of hedge fund 1, 4, 5, 8, 9 and 10 and are not statistically significant in the cases of hedge fund 1 and 8 at the 5% significance level, respectively. We have a covariance stationary model, if the sum of the estimated GARCH(1) parameter and the estimated ARCH(1) parameter is close to one $(a_i + b_i) < 1$.

RESIDUAL DIAGNOSTICS				
	JARQUE-BERA TEST	**LJUNG-BOX TEST (AUTOCORRELATION)**	**LJUNG-BOX TEST (HETEROSKEDASTICITY)**	**LAGRANGE-MULTIPLIER TEST**
HF1	2,457 (0,2927)	13,1194 (0,3604)	8,0368 (0,7822)	10,47 (0,575)
HF2	9,2292* (0,0099)	8,8665 (0,7143)	10,741 (0,5512)	11,96 (0,5512)
HF3	7,2988* (0,026)	15,3637 (0,2221)	9,7842 (0,6349)	9,784 (0.6349)
HF4	1,9885 (0,37)	17,4129 (0,1347)	18,1607 (0,1109)	15,02 (0,2406)
HF5	11,3645* (0,0034)	11,0961 (0,5207)	5,6596 (0,9323)	6,944 (0,858)
HF6	1,4863 (0,4756)	10,0311 (0,6132)	12,3511 (0,4179)	13,64 (0,3242)
HF7	0,8766 (0,6451)	3,5662 (0,9901)	4,7047 (0,9671)	4,489 (0,9671)
HF8	39,5719* (0,0000)	11,2666 (0,5062)	4,9655 (0,9591)	4,181 (0.9799)
HF9	3,2014 (0,2018)	12,4663 (0,409)	6,9525 (0,8607)	9,601 (0,5609)
HF10	11,963* (0,0025)	21,1142* (0,0487)	12,537 (0,4036)	16,25 (0,1799)

Table 7.14: Residual diagnostics of the single factor GARCH(1,1) model.

The Jarque-Bera and the Ljung-Box tests for the standardized residuals and the Ljung-Box and the LM tests for the squared standardized residuals as well as their p-values, which are in the brackets. With (*), we denote the quantities which are statistically significant at the 5% significance level.

The null of hypothesis of the Jarque-Bera test suggests that there is normality in the standardized residuals. From the single factor GARCH model, we concluded that the normality, in the residual series, is rejected at the 5% significance level in regard to hedge fund 2, 3, 5, 8 and 10.

If the model is successful modeling the autocorrelation structure in the conditional mean and conditional variance, then there should be no autocorrelation left in the standardized residuals and squared standardized residuals. For this reason, we proceed to the application of the Ljung-Box test. The null hypothesis of the Ljung-Box test when we want to test for the existence of autocorrelation in the standardized residuals refers to no autocorrelation. The null hypothesis slightly rejected in hedge fund 10, which has value of alpha 21.12 and p-value 0.0487.

Additionally, we apply the Ljung-Box test seeking for the existence of heteroskedasticity to the standardized residuals, i.e autocorrelation between the squared standardized residuals. The null hypothesis refers to no heteroskedasticity. Looking at table 7.14, we conclude that there is no heteroskedasticity to the standardized residuals at the 5% significance level.

Furthermore, we test if there are any ARCH effects left, after the application of the GARCH(1,1) model, applying the Lagrange Multiplier (LM) test on the standardized residuals. The null hypothesis asserts that there are no ARCH effects on the standardized residuals. Consequently, we observe that there are no ARCH effects left after the application of the single factor GARCH(1,1) model.

7.9 Three factor GARCH model

We apply a three factor GARCH(1,1) model, with conditional mean equation such as: $R_{it} = \alpha_{it} + \beta_{1,t} \times R_{RUS,t} + \beta_{2,t} \times R_{SMB,t} + \beta_{3,t} \times R_{HML,t} + \varepsilon_{it}$ (7.7), where R_{it} is the return on hedge fund i at time t, α_{it} is the abnormal performance of the hedge fund i at time t, $\beta_{1,t}$, $\beta_{2,t}$ and $\beta_{3,t}$ are the slope coefficients or the factor loadings of hedge fund i at time t, $R_{RUS,t}$ is the return on the Russell 3000 equity index at time t, $R_{SMB,t}$ is the return on factor mimicking portfolio for size at time t, $R_{HML,t}$ is the return on factor mimicking portfolio for book-to-market equity index at time t and ε_{it} is the error term of the hedge fund i at time t. The conditional variance equation is $\sigma_t^2 = a_0 + a_1\varepsilon_{t-1}^2 + b_1\sigma_{t-1}^2$ (7.8), where a_0 denotes the constant in the conditional variance equation, a_1 denotes the estimated ARCH(1) parameter and b_1 denotes the estimated GARCH(1) parameter. Specifically, we apply this model ten times, once for each hedge fund. In table 7.15, we obtain the coefficients of alpha, beta, a_0, a_1 and b_1, as well as their p-values, in each case.

THREE FACTOR GARCH(1,1) MODEL							
	ALPHA	**BETA1**	**BETA2**	**BETA3**	**A**	**ARCH(1)**	**GARCH(1)**
HF1	0,0065* (0,0002)	0,1949* (0,0000)	-0,08 (0,0506)	-0,0085 (0,3931)	-0,0003 (0,448)	2,5117* (0,0004)	0,072 (0,1882)
HF2	0,004 (0,242)	1,198* (0,0000)	0,8677* (0,0000)	-0,4699* (0,0000)	0,0019 (0,367)	-0,0327 (0,3988)	0,0117 (0,4985)
HF3	0,0163* (0,0222)	0,5358* (0,0004)	0,3013 (0,0815)	0,1334 (0,1988)	0,0009* (0,0223)	0,3547 (0,0688)	0,4471* (0,0115)
HF4	0,0087 (0,0551)	0,5878* (0,0000)	0,8167* (0,0000)	-0,2686* (0,0225)	0,0008 (0,0634)	0,3588* (0,0029)	0,4766* (0,0091)
HF5	0,0053* (0,0395)	0,0149 (0,4133)	0,251* (0,0021)	-0,0943 (0,1086)	0,0002* (0,0129)	0,9945* (0,0003)	0,2958* (0,0003)
HF6	0,0128* (0,0114)	0,318* (0,002)	0,3495* (0,0145)	0,0205 (0,4233)	-0,0001 (0,3106)	-0,0637 (0,1308)	1,0788* (0,0000)
HF7	0,0094* (0,0221)	0,2372* (0,0021)	-0,2843* (0,0133)	0,1234 (0,0846)	0,0004 (0,2584)	0,2539 (0,1737)	0,5315 (0,1407)
HF8	0,007 (0,1582)	0,2085* (0,0345)	0,4995* (0,0000)	-0,4278* (0,0000)	0,0012* (0,024)	0,3453* (0,0472)	0,2002 (0,2067)
HF9	0,0042 (0,0607)	0,0792 (0,0502)	0,1229* (0,0211)	-0,2421* (0,0000)	-0,0006 (0,1221)	-0,0238 (0,0572)	1,0155* (0,0000)
HF10	0,0029 (0,2739)	0,3163* (0,0002)	0,3941* (0,0006)	0,2406* (0,007)	0,0013 (0,3252)	-0,052 (0,3259)	0,1676 (0,4655)

Table 7.15: Coefficients of the three factor GARCH(1,1) model.

The results of a single factor model for the 10 hedge funds. In the brackets, there are the corresponding p-values of alphas, betas, a_0, a_1 and b_1. With (*), we denote the quantities which are statistically significant at the 5% significance level.

The quantity of interest is the significance of alphas ($\alpha_{i,t}$), which are the intercepts in the regressions of the fund's excess returns on the excess returns of Russell 3000 equity index (RUS), on the excess returns of the factor mimicking portfolio for size (SMB) and on the excess returns of the factor mimicking portfolio for boot-to-market equity (HML). We apply t-tests, at which the null hypothesis asserts that the alpha coefficient is equal to zero. Checking from the table the alpha's p-values, we conclude that hedge fund 1, 3, 5, 6 and 7 have statistically significant alpha at the 5% significance level. Hedge fund 3 seems to perform the best, because it has alpha equal to 0.0163 (p-value: 0.0222), followed by hedge fund 6, which has value of alpha equal to 0.0128 (p-value: 0.0144). Consequently, we can comprehend these hedge funds to our portfolio.

We also apply t-tests in order to test the significance of the beta coefficients. The null hypothesis maintains that the beta coefficient is equal to zero. From the table, we can conclude that hedge fund 1, 2, 3, 4, 6, 7, 8 and 10 load significantly positive on the Russell 3000 equity index at the 5% significance level. Hedge fund 2, 4, 5, 6, 8, 9 and 10 load significantly positive on the factor mimicking portfolio for size (SMB) and hedge fund 7 loads significantly negative on the same factor at the 5% significance level. Hedge fund 10 loads significantly positive on the factor mimicking portfolio for book-to-market equity (HML) and hedge fund 2, 4, 8 and 9 load significantly negative on the same factor at the 5% significance level.

We continue applying t-test and we conclude that the a_0's, which represent the constant in the conditional variance equation, are statistically significant in regard to hedge fund 3, 5 and 8, at the 5% significance level. Continuously, the a_1's, which represent the estimated ARCH(1) parameters, are statistically significant in the cases of hedge fund 1, 4, 5 and 8 at the 5% significance level. Finally, the b_1's, which represent the estimated GARCH(1) parameters, are statistically significant in the cases of hedge fund 3, 4, 5, 6 and 9. We have a covariance stationary model, if the sum of the estimated GARCH(1) parameter and the estimated ARCH(1) parameter is close to one $(a_i + b_i) < 1$.

RESIDUAL DIAGNOSTICS				
	JARQUE-BERA TEST	**LJUNG-BOX TEST (AUTOCORRELATION)**	**LJUNG-BOX (HETEROSKEDASTICITY)**	**LAGRANGE-MULTIPLIER TEST**
HF1	2,6054 (0,2718)	14,8084 (0,2521)	7,6308 (0,8133)	12,2629 (0.4244)
HF2	0,3464 (0,841)	15,8882 (0,1964)	5,8851 (0,9218)	5,564 (0,9364)
HF3	7,8272* (0,02)	12,5818 (0,4002)	10,5525 (0,5676)	13,1577 (0,3577)
HF4	2,1988 (0,3331)	14,9679 (0,2432)	12,732 (0,3888)	13,5959 (0,3273)
HF5	13,4476* (0,0012)	12,8124 (0,3828)	3,7648 (0,9873)	4,235 (0,9788)
HF6	2,2299 (0,3279)	6,7283 (0,875)	13,6405 (0,3243)	13,0144 (0,368)
HF7	1,3434 (0,5108)	6,5059 (0,8885)	1,1461 (0.9876)	2,3318 (0,9987)
HF8	3,6447 (0,1616)	17,7993 (0,1219)	8,8473 (0,7159)	8,2303 (0,7669)
HF9	2,2938 (0,3176)	11,2679 (0,5061)	12,7358 (0,3885)	18,2493 (0,1083)
HF10	16,2784* (0,0003)	3,9171 (0,9849)	14,4548 (0,2726)	21,7956* (0,039)

Table 7.16: Residual diagnostics of the three factor GARCH(1,1) model.

The Jarque-Bera and the Ljung-Box tests for the standardized residuals and the Ljung-Box and the LM tests for the squared standardized residuals as well as their p-values, which are in the brackets. With (*), we denote the quantities which are statistically significant at the 5% significance level.

In the following (table 7.16), we proceed to test the significance of the null hypothesis of the Jarque-Bera test, which refers that there is normality in the residuals series. Specifically, we apply this test and we conclude that the null hypothesis of normality is rejected in the cases of hedge fund 3, 5 and 10 at the 5% significance level.

We apply the Ljung-Box test to the standardized residuals in order to detect the autocorrelation between them and the same test to the squared standardized residuals in order to detect heteroskedasticity in the standardized residuals. In the first case, the null hypothesis refers to no autocorrelation and the second case, it refers to no heteroskedasticity. Finally, examining the results from table 7.16, we can conclude that there is no autocorrelation, neither heteroskedasticity. We hypothesize that every model is adequately fitted.

Furthermore, we test if there are any ARCH effects left after the application of the GARCH(1,1) model. So, we apply the LM test in the standardized residuals. The null hypothesis maintains that there are no ARCH effects on the standardized residuals. We observe that there are no ARCH effects after the application of the three factor GARCH(1,1) model, apart from hedge fund 10, which has value of LM statistic 21.7956 with p-value equal to 0.039.

7.10 Four factor GARCH model

We apply four factor GARCH (1,1) models, with conditional mean equation with the concretely type of formulation, such as: $R_{it} = \alpha_{it} + \beta_{1,t} \times R_{RUS,t} + \beta_{2,t} \times R_{SMB,t} + \beta_{3,t} \times R_{HML,t} + \beta_{4,t} \times R_{MOM,t} + \varepsilon_{it}$ (7.8), where R_{it} is the return on hedge fund i at time t, α_{it} is the abnormal performance of the hedge fund i at time t, $\beta_{1,t}$, $\beta_{2,t}$, $\beta_{3,t}$ and $\beta_{4,t}$ are the slope coefficients or the factor loadings of hedge fund i at time t, $R_{RUS,t}$ is the return on the Russell 3000 equity index at time t, $R_{SMB,t}$ is the return on the factor mimicking portfolio for size at time t, $R_{HML,t}$ is the return on factor mimicking portfolio for book-to-market equity at time t and $R_{MOM,t}$ is the return on the momentum factor at time t and ε_{it} is the error term of the hedge fund i at time t. The conditional variance equation is $\sigma_t^2 = a_0 + a_1\varepsilon_{t-1}^2 + b_1\sigma_{t-1}^2$ (7.9), where a_0 (A in the table) denotes the constant in the conditional variance equation, a_1 denotes the estimated ARCH(1) parameter and b_1 denotes the estimated GARCH(1) parameter. Specifically, we apply this model ten times, once for each hedge fund. In table 7.17, we obtain the coefficients of alpha, beta, a_0, a_1 and b_1, as well as their p-values, in each case.

FOUR FACTOR GARCH(1,1) MODEL								
	ALPHA	**BETA1**	**BETA2**	**BETA3**	**BETA4**	**A**	**ARCH(1)**	**GARCH(1)**
HF1	0,0084* (0,0029)	0,1144* (0,0021)	-0,0943* (0,0087)	-0,0865* (0,0462)	-0,0497* (0,0005)	0,00003 (0,4795)	2,5388* (0,0005)	0,0833 (0,113)
HF2	0,011* (0,0079)	0,909* (0,0000)	0,6168* (0,0000)	-0,8802* (0,0000)	-0,3593* (0,0000)	0,0017 (0,1811)	-0,1083 (0,1915)	-0,0168 (0,4947)
HF3	0,0124 (0,0693)	0,7237* (0,0001)	0,472* (0,0377)	0,436* (0,0369)	0,2534* (0,0203)	0,0008* (0,0364)	0,3116 (0,074)	0,4738* (0,0049)
HF4	0,006 (0,1499)	0,6468* (0,0000)	0,8879* (0,0000)	-0,1156 (0,2356)	0,181* (0,0376)	0,0007 (0,0677)	0,3684* (0,0029)	0,4896* (0,0048)
HF5	0,0034 (0,133)	0,0733 (0,1756)	0,3423* (0,0001)	0,0368 (0,3434)	0,1317* (0,007)	0,0002* (0,0189)	1,1595* (0,0002)	0,2662* (0,0005)
HF6	0,0184* (0,001)	0,1701 (0,0567)	0,137 (0,1872)	-0,2021 (0,0794)	-0,1996* (0,0079)	-0,00007 (0,337)	-0,0352 (0,3093)	1,0307* (0,0000)
HF7	0,0072 (0,0578)	0,3201* (0,0012)	-0,2173* (0,0497)	0,2434* (0,03)	0,1176 (0,1407)	0,0005 (0,2493)	0,2116 (0,1869)	0,5358 (0,1473)
HF8	0,0036 (0,2987)	0,3372* (0,0105)	0,5767* (0,0000)	-0,2349 (0,0511)	0,1289 (0,0713)	0,0011* (0,013)	0,3695* (0,0358)	0,1928 (0,1971)
HF9	0,0051 (0,0681)	0,0467 (0,2304)	0,1125 (0,1199)	-0,3107* (0,0005)	-0,0488 (0,1629)	-0,00003 (0,2088)	-0,0302 (0,0901)	1,0269* (0,000)
HF10	0,0005 (0,4606)	0,4569* (0,0000)	0,5194* (0,0001)	0,4299* (0,001)	0,1716* (0,0119)	0,0013 (0,2989)	-0,0703 (0,29)	0,1234 (0,4728)

Table 7.17: Coefficients of the four factor GARCH(1,1) model.

The results of the single factor models of the ten hedge funds. In the brackets, there are the corresponding p-values of alphas, betas, a_0, a_1 and b_1. With (*), we denote the quantities which are statistically significant at the 5% significance level.

The quantity of interest is the significance of alphas ($\alpha_{i,t}$), which are the intercepts in the regressions of the fund's excess returns on the excess returns of Russell 3000 equity index (RUS), on the excess returns of the factor mimicking portfolio for size (SMB), on the excess returns of the factor mimicking portfolio for equity book-to-market (HML) and on the excess returns of the momentum factor (MOM). We apply t-test, which null hypothesis asserts that the alpha coefficient is equal to zero. Looking at the table, the alpha's p-values, we conclude that hedge fund 1, 2 and 6 are statistically significant at the 5% significance level. Hedge fund 6 seems to perform the best, because it has alpha equal to 0.0184 (p-value: 0.001), followed by hedge fund 2, which has value of alpha equal to 0.011 (p-value: 0.0079). Consequently, we comprehend these hedge funds to our portfolio.

We, also, apply t-tests in order to test the significance of the beta coefficients. The null hypothesis refers that the beta coefficient is equal to zero. Looking at the table, we observe that hedge fund 1, 2, 3, 4, 7, 8 and 10 load significantly positive on the Russell 3000 equity index at the 5% significance level. Hedge fund 2, 3, 4, 5, 8 and 10 load significantly positive on the factor mimicking portfolio for size and hedge fund 1 and 7 load significantly negative on the same factor at the 5% significance level. Hedge fund 3, 7 and 10 load significantly positive on the factor mimicking portfolio for book-to-market equity and hedge fund 1, 2 and 9 load significantly negative on the same factor at the 5% significance level. Hedge fund 3, 4, 5 and 10 load significantly positive on the momentum factor and hedge fund 1, 2 and 6 load significantly negative on the same factor at the 5% significance level.

We apply t-test in order to test the statistically significance of the a_0's, a_1's and b_1's coefficients. We conclude that a_0's, which represent the constant in the conditional variance equation, are statistically significant in regard to hedge fund 3, 5 and 8 at the 5% significance level. Continuously, a_1's, which represent the estimated ARCH(1) parameters, are statistically significant in the cases of hedge fund 1, 4, 5 and 8 at the 5% significance level. Finally, b_1's, which represent the estimated GARCH(1) parameters, are statistically significant in the cases of hedge fund 3, 4, 5, 6 and 9. We have a covariance stationary model, if the sum of the estimated GARCH(1) parameter and the estimated ARCH(1) parameter is close to one $(a_i + b_i) < 1$.

RESIDUAL DIAGNOSTICS				
	JARQUE-BERA TEST	**LJUNG-BOX TEST (AUTOCORRELATION)**	**LJUNG-BOX TEST (HETEROSKEDASTICITY)**	**LAGRANCE-MULTIPLIER TEST**
HF1	1.775 (0.4116)	6.032 (0.9145)	6.889 (0.8649)	15.66 (0.2073)
HF2	0.9984 (0.607)	7.827 (0.7985)	3.531 (0.9905)	3.554 (0.9902)
HF3	3.83 (0.1474)	14.92 (0.2459)	12.07 (0.4397)	15.17 (0.2321)
HF4	3.138 (0.2082)	15.61 (0.2099)	13.71 (0.3195)	14.53 (0.2679)
HF5	8.467* (0.0145)	12.02 (0.4441)	5.999 (0.9161)	6.301 (0.9002)
HF6	2.079 (0.3537)	7.261 (0.8399)	14.84 (0.2505)	10.88 (0.5395)
HF7	0.8775 (0.6448)	9.163 (0.6889)	1.57 (0.9998)	2.069 (0.9993)
HF8	3.942 (0.1393)	20.45 (0.05899)	7.441 (0.8272)	7.248 (0.8408)
HF9	2.39 (0.3028)	13.7 (0.3203)	14.17 (0.2902)	18.08 (0.1134)
HF10	6.937* (0.03116)	5.368 (0.9446)	14.65 (0.261)	18.67 (0.09693)

Table 7.18: Residual diagnostics of the four factor GARCH(1,1) model.

The Jarque-Bera and the Ljung-Box tests for the standardized residuals and the Ljung-Box and the LM tests for the squared standardized residuals as well as their p-values, which are in the brackets. With (*), we denote the quantities which are statistically significant at the 5% significance level.

In the following (table 7.18), we proceed to test the significance of the null hypothesis, which refers that there is normality in the residuals series. Specifically, we apply the Jarque-Bera test and we conclude that the null hypothesis of normality is rejected in the cases of hedge fund 5 and 10 at the 5% significance level.

We apply the Ljung-Box test to the standardized residuals in order to detect the autocorrelation between them and the same test to the squared standardized residuals in order to detect heteroskedasticity in the standardized residuals. In the first case, the null hypothesis refers to no autocorrelation and the second case, it refers to no heteroskedasticity. Finally, examining the results from the table, we can conclude that there is no autocorrelation neither heteroskedasticity. We hypothesize that the model is adequately fitted.

Furthermore, we test if there are any ARCH effects left after the application of the GARCH(1,1) model. So, we apply the LM test in the standardized residuals. The null hypothesis maintains that there are no ARCH effects on the standardized residuals. We observe that there are no ARCH effects after the application of the four factor GARCH(1,1) model.

7.11 Multifactor GARCH model

We have 14 market indices that can be used in our models. In order to select the suitable set of market indices, we use the backward selection approach. We proceed to this action because we want to take safe conclusions relative to the evaluation of the hedge funds' performance.

Our model has the following conditional mean equation: $R_{it} = \alpha_i + \sum_{k=1}^{K} \beta_k F_{kt} + \varepsilon_{it}$ (7.10), where R_{it} is the return of a hedge fund investment at time t, α_i is the abnormal performance of the hedge fund i at time t which is an aggregate measure of performance, β_k is the loading of risk factor k associated with the hedge fund i, F_{kt} is the excess return of factor k at time t and ε_{it} is the error term of hedge fund i at time t. The conditional variance equation has the following expression: $\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + b_1 \sigma_{t-1}^2$ (7.11) GARCH(1,1), where α_0 (A in table 7.19) denotes the constant in the conditional variance equation, α_1 denotes the estimated ARCH(1) parameter and b_1 denotes the estimated GARCH(1) parameter. Specifically, we apply this model ten times, once for each hedge fund. We use the same 14 market indices.

Below, we present the regressions that have arisen after the backward selection approach for each hedge fund.

Hedge fund 1:

$$R_{it} = \alpha_{it} + \beta_{1,i} XR_{RUS,t} + \beta_{2,i} XR_{RUS1,t} + \beta_{3,i} XR_{SMB,t} + \beta_{4,i} XR_{HML,t} + \beta_{5,i} XR_{SBWG,t} + \beta_{6,i} XR_{LHY,t} + \beta_{7,i} XR_{DEFSPR,t} + \beta_{8,i} XR_{GSCI,t} + \varepsilon_{it}$$

Hedge fund 2:

$$R_{it} = \alpha_{it} + \beta_{1,i} XR_{RUS,t} + \beta_{2,i} XR_{SMB,t} + \beta_{3,i} XR_{HML,t} + \beta_{4,i} XR_{MOM,t} + \beta_{5,i} XR_{SBWG,t} + \varepsilon_{it}$$

Hedge fund 3:

$$R_{it} = \alpha_{it} + \beta_{1,i} XR_{RUS,t} + \beta_{2,i} XR_{RUS1,t} + \beta_{3,i} XR_{MXUS,t} + \beta_{4,i} XR_{MEM,t} + \beta_{5,i} XR_{SMB,t} + \beta_{6,i} XR_{HML,t} + \beta_{7,i} XR_{MOM,t} + \beta_{8,i} XR_{LHY,t} + \beta_{9,i} XR_{FRBI,t} + \varepsilon_{it}$$

Hedge fund 4:

$$R_{it} = \alpha_{it} + \beta_{1,i} XR_{RUS,t} + \beta_{2,i} XR_{RUS1,t} + \beta_{3,i} XR_{SMB,t} + \beta_{4,i} XR_{HML,t} + \varepsilon_{it}$$

Hedge fund 5:

$$R_{it} = \alpha_{it} + \beta_{1,i}\, XR_{RUS,t} + \beta_{2,i}\, XR_{SMB,t} + \beta_{3,i}\, XR_{MOM,t} + \beta_{4,i}\, XR_{VIX,t} + \varepsilon_{it}$$

Hedge fund 6:

$$R_{it} = \alpha_{it} + \beta_{1,i}\, XR_{MXUS,t} + \beta_{2,i}\, XR_{SMB,t} + \beta_{3,i}\, XR_{MOM,t} + \varepsilon_{it}$$

Hedge fund 7:

$$R_{it} = \alpha_{it} + \beta_{1,i}\, XR_{RUSl,t} + \beta_{2,i}\, XR_{MEM,t} + \beta_{3,i}\, XR_{SMB,t} + \beta_{4,i}\, XR_{SBGC,t} + \beta_{5,i}\, XR_{DEFSPR,t} + \varepsilon_{it}$$

Hedge fund 8:

$$R_{it} = \alpha_{it} + \beta_{1,i}\, XR_{RUS,t} + \beta_{2,i}\, XR_{RUSl,t} + \beta_{3,i}\, XR_{SMB,t} + \beta_{4,i}\, XR_{MOM,t} + \beta_{5,i}\, XR_{VIX,t} + \varepsilon_{it}$$

Hedge fund 9:

$$R_{it} = \alpha_{it} + \beta_{1,i}\, XR_{RUS,t} + \beta_{2,i}\, XR_{MXUS,t} + \beta_{3,i}\, XR_{HML,t} + \beta_{4,i}\, XR_{MOM,t} + \beta_{5,i}\, XR_{FRBI,t} + \varepsilon_{it}$$

Hedge fund 10:

$$R_{it} = \alpha_{it} + \beta_{1,i}\, XR_{MEM,t} + \beta_{2,i}\, XR_{SMB,t} + \beta_{3,i}\, XR_{HML,t} + \beta_{4,i}\, XR_{DEFSPR,t} + \beta_{5,i}\, XR_{FRBI,t} + \varepsilon_{it}$$

In table 7.19, we obtain the coefficients of alpha, beta, α_0, α_1 and b_1, as well as their p-values, in each case.

MULTIFACTOR GARCH(1,1) MODEL										
	HF1	**HF2**	**HF3**	**HF4**	**HF5**	**HF6**	**HF7**	**HF8**	**HF9**	**HF10**
ALPHA	0.0129* (0.0001)	0.0117* (0.0047)	0.0034 (0.228)	0.0066 (0.0984)	0.0002 (0.4838)	0.0182* (0.0001)	0.0074* (0.0167)	0.0043 (0.1773)	0.013* (0.0009)	0.0042 (0.1079)
RUS	0.1796 (0.0001)	0.8874 (0.0000)	0.8279 (0.0001)	0.5772 (0.0074)	0.2749 (0.0293)			0.8016 (0.0000)	-0.3099 (0.02)	
RUS1	0.1851 (0.0076)		-0.2222 (0.0021)	0.3037 (0.0179)			0.3661 (0.0083)	0.3029 (0.0003)		
MXUS			-0.7925 (0.0001)			0.1719 (0.0402)			0.3879 (0.0075)	
MEM			0.6143 (0.0011)				0.1959 (0.0003)			0.2688 (0.0001)
SMB	0.3202 (0.001)	0.5878 (0.0021)	0.7 (0.0001)	0.6322 (0.0005)	0.2999 (0.0071)		-0.389 (0.0003)	0.467 (0.0013)		0.1882 (0.0199)
HML	-0.1846 (0.0002)	-0.9222 (0.0000)	0.7485 (0.00002)	-0.3934 (0.0031)		-0.2394 (0.0209)			-0.3976 (0.0000)	0.195 (0.0027)
MOM		-0.3706 (0.0000)	0.3794 (0.0002)		0.2869 (0.0000)	-0.2505 (0.0005)		0.2513 (0.002)	-0.0991 (0.0077)	
SBGC							0.7122 (0.0156)			
SBWG	-0.5596 (0.0000)	-0.3291 (0.0466)								
LHY	-0.1009 (0.0108)		-0.4324 (0.0029)							
DEFSPR	7.66 (0.0000)						9.6893 (0.0011)			7.2811 (0.0067)
FRBI			-0.7279 (0.0456)						0.7195 (0.0291)	0.7041 (0.0043)
GSCI	0.0867 (0.0001)									
VIX					0.319 (0.0123)			0.5251 (0.0003)		
A	0.0014 (0.4731)	0.0016 (0.2571)	0.0005* (0.0063)	0.0011* (0.0386)	0.0004* (0.0017)	-0.0001 (0.2085)	0.0005 (0.0514)	0.0004 (0.1006)	0.0007 (0.4831)	0.00004 (0.3173)
ARCH(1)	2.365* (0.0015)	-0.1111 (0.1808)	-0.2492* (0.0000)	0.4271* (0.0029)	0.9177* (0.0095)	-0.0002 (0.4991)	0.5791 (0.0647)	0.8034* (0.0033)	-0.06214 (0.1246)	0.5252* (0.0134)
GARCH(1)	0.0088 (0.4431)	0.0223 (0.4947)	1.0123* (0.0000)	0.3474 (0.0508)	0.2741* (0.0244)	1.01* (0.0000)	0.0803 (0.3943)	0.2149 (0.0889)	1.039* (0.0000)	0.5549* (0.0004)

Table 7.19: Coefficients of the multi-factor GARCH(1,1) model.

The results of the applied multifactor GARCH(1,1) models, which have arisen by the backward procedure, of the ten hedge funds. In the brackets, there are the corresponding p-values of the alphas, betas, a_0 's, a_1 's and b_1 's. With (*), we denote the quantities that are statistically significant at the 5% significance level (in regard to the alpha coefficients, ARCH(1), GARCH(1,1) coefficients). All beta coefficients, which we accomplish in the table, are statistically significant at the 5% significance level.

We apply t-tests in order to test the significance of the alpha coefficients, which have arisen from the application of the regression with the general form (7.10). The null hypothesis refers that the alpha coefficient is equal to zero. Looking at table 7.19, we summarize that the alpha coefficients are statistically significant only in the cases of hedge fund 1, 2, 6, 7 and 9 at the 5% significance level. Hedge fund 6 seems to perform the best, because it has alpha equal to 0.0182 (p-value: 0.0001), followed by hedge fund 9, which has value of alpha equal to 0.013 (p-value: 0.0009). Consequently, we comprehend these hedge funds to our portfolio.

We also apply t-tests in order to test the significance of the beta coefficients. The null hypothesis refers that the beta coefficient is equal to zero. Checking the results from the table, we conclude that hedge fund 1, 2, 3, 4, 5 and 8 load significantly positive on the factor Russell 3000 equity index (RUS) and hedge fund 9 loads significantly negative on the same factor at the 5% significance level. Hedge fund 1, 4, 7 and 8 load significantly positive on the Russell 3000 equity index excess return lagged once (RUS1) and hedge fund 3 loads significantly negative on the same factor at the 5% significance level. Hedge fund 6 and 9 load significantly positive on the Morgan Stanley Capital International world excluding USA index (MXUS) and hedge fund 3 loads significantly negative on the same factor at the 5% significance level. Hedge fund 3, 7 and 9 load significantly positive on the Morgan Stanley Capital International emerging markets (MEM) at the 5% significance level. Hedge fund 1, 2, 3, 4, 5, 8 and 10 load significantly positive on the factor mimicking portfolio for size (SMB) and hedge fund 7 loads significantly negative on the same factor at the 5% significance level. Hedge fund 3 and 10 load significantly positive on the factor mimicking portfolio for book-to-market equity (HML) and hedge fund 1, 2, 4, 6 and 9 load significantly negative on the same factor at the 5% significance level. Hedge fund 3, 5 and 8 load significantly positive on the momentum factor (MOM) and hedge fund 2, 6 and 9 load significantly negative on the same factor at the 5% significance level. Hedge fund 7 loads significantly positive on the Salomon Brothers and corporate bond (SBGC) at the 5% significance level. Hedge fund 1 and 2 load significantly negative on the Salomon Brothers world government bond index (SBWG) at the 5% significance level. Hedge fund 1 and 3 load significantly negative on the Lehman high yield index (LHY) at the 5% significance level. Hedge fund 1, 7 and 10 load significantly positive on the difference between the yield on the BAA-rated corporate bonds and the 10-year Treasury bonds (DEFSPR) at the 5% significance level. Hedge fund 9 and 10 load significantly positive on the Federal Reserve Bank competitiveness weighted dollar index (FRBI) and hedge fund 3 loads significantly negative on the same factor at the 5%

significance level. Hedge fund 1 loads significantly positive on the Goldman Sachs commodity index (GSCI) at the 5% significance level. Hedge fund 5 and 8 load significantly positive on the change in S&P 500 implied volatility index (VIX) at the 5% significance level.

Using t-tests, we conclude that the α_0's, which represent the constant in the conditional variance equation, are statistically significant in the cases of hedge fund 3, 4 and 5 at the 5% significance level. In the following, the α_1's, which represent the estimated ARCH(1) parameter, are statistically significant in the cases of hedge fund 1, 3, 4, 5, 8 and 10 at the 5% significance level. In regard to the b_1's, which represent the estimated GARCH(1) parameter, they are statistically significant in the cases of hedge fund 3, 5, 6, 9 and 10 at the 5% significance level. We have a covariance stationary model, if the sum of the estimated GARCH(1) parameter and the estimated ARCH(1) parameter is close to one $(a_i + b_i) < 1$.

RESIDUAL DIAGNOSTICS				
	JARQUE-BERA TEST	**LJUNG-BOX TEST (AUTOCORRELATION)**	**LJUNG-BOX (HETEROSKEDASTICITY)**	**LAGRANGE-MULTIPLIER TEST**
HF1	1.483 (0.4764)	10.68 (0.5562)	8.946 (0.7075)	10.39 (0.5817)
HF2	1.198 (0.5494)	7.095 (0.8513)	4.252 (0.9784)	3.824 (0.9864)
HF3	0.6904 (0.7081)	15.65 (0.208)	10.36 (0.5848)	7.809 (0.7999)
HF4	1.491 (0.4745)	11.24 (0.5084)	11.5 (0.4867)	11.18 (0.5137)
HF5	40.3* (0.0000)	9.097 (0.6946)	8.61 (0.7358)	7.879 (0.7945)
HF6	1.608 (0.4475)	7.778 (0.8022)	12.1 (0.4379)	10.38 (0.5823)
HF7	1.172 (0.5566)	4.353 (0.9762)	12.98 (0.3704)	8.217 (0.768)
HF8	1.166 (0.5583)	8.857 (0.7151)	7.384 (0.8312)	8.122 (0.7756)
HF9	0.7231 (0.6966)	13.28 (0.3487)	7.912 (0.792)	9.873 (0.6271)
HF10	4.116 (0.1277)	11.5 (0.4868)	7.921 (0.7913)	10.96 (0.5322)

Table 7.20: Residual diagnostics of the multi-factor GARCH(1,1) model.

The Jarque-Bera and the Ljung-Box tests for the standardized residuals and the Ljung-Box and the LM tests for the squared standardized residuals as well as their p-values, which are in the brackets. With (*), we denote the quantities which are statistically significant at the 5% significance level.

In the following (table 7.20), we proceed to test the significance of the null hypothesis of the Jarque-Bera test, which refers that there is normality in the residuals series. Specifically, we apply this test and we conclude that the null hypothesis of normality is rejected only in one case of hedge fund 5 at the 5% significance level.

We apply the Ljung-Box test to the standardized residuals in order to detect the autocorrelation between them and the same test to the squared standardized residuals in order to detect heteroskedasticity in the standardized residuals. In the first case, the null hypothesis refers to no autocorrelation and the second case, it refers to no heteroskedasticity. Finally, examining the results from the table, we can conclude that there is no autocorrelation, neither heteroskedasticity in the standardized residuals. We hypothesize that the model is adequately fitted.

Furthermore, we test if there are any ARCH effects left, applying the LM test in the standardized residuals. The null hypothesis maintains that there are no ARCH effects in the standardized residuals after the application of GARCH(1,1) model. Finally, we conclude that there are no ARCH effects left.

7.12 Portfolio evaluation

In this chapter, we calculate some measures in order to evaluate our portfolios. In particular, we applied single factor, three factor, four factor and multifactor models (the last have arisen by following a backward selection approach). These models gave us that hedge fund 1 and 6 have the highest values of alphas and seem to perform better than the other hedge funds. So, we constructed four equally-weighted portfolios, each of one comprehend hedge fund 1 and 6.

In contrary to these results, when we applied the single and three factor models including the GARCH(1,1) model, we received that hedge fund 3 and 6 perform better than the others. As a result, we constructed two portfolios, which comprised hedge fund 3 and 6. When we applied the four factor models including the GARCH(1,1) model, we received that hedge fund 2 and 6 perform better than the others. Consequently, we constructed one portfolio, which comprised hedge fund 2 and 6. Finally, we applied multifactor GARCH models, following the backward selection approach in order to select the most suitable set of market indices, in each case. These models suggested that hedge fund 6 and 9 perform better than the other hedge funds. Thus, we constructed one portfolio, which comprehended hedge fund 6 and 9.

The data from the last year of each hedge fund is used in the out-of-sample analysis. With these realized returns we calculate the mean return, the standard deviation, the annualized return, the cumulative return and the Sharpe ratio. We used as index benchmark, the Russell 3000 equity index, in order to calculate the success rate, the information ratio and the semi-deviation.

	PORTFOLIO 1, 2, 3, 4	PORTFOLIO 5, 6	PORTFOLIO 7	PORTFOLIO 8
	HF1 & HF6	HF3 & HF6	HF2 & HF6	HF6 & HF9
MEAN RETURN	0.005	0.0088	0.0131	0.0081
STANDARD DEVIATION	0.0265	0.0314	0.0505	0.0231
ANNUALIZED RETURN	0.0596	0.1051	0.1578	0.0975
CUMULATIVE RETURN	0.1192	0.2102	0.3155	0.195
SUCCESS RATE	0.4167	0.4583	0.625	0.5
SHARPE RATIO	0.1874	0.2785	0.2603	0.3517
INFORMATION RATIO	-1.7892	1.9488	4.3701	1.6945
SEMI-DEVIATION	0.0771	0.0929	0.153	0.0655

Table 7.21: Comparison of portfolios.

The results of the mean return, standard deviation, annualized return, cumulative return, success rate, Sharpe ratio, information ratio and semi-deviation for the portfolios. The second line of this table concludes the best performing hedge funds in each case.

We use the standard deviation of the returns because it is one of the best-known measures for risk.

The annualized return is evaluated by the multiplication of mean return with 12 (months) or 252 (trading days). Specifically, $r_{an} = r_{it} \times 12$, where r_{it} is the monthly return of hedge fund i at time t.

The cumulative return is the return of T periods which is given by $r_t(T) = r_{i,t} + r_{i,t-1} + \ldots + r_{i,t-T+1}$, where r_{it} is the monthly return of hedge fund i at time t.

Success rate gives us the percentage for which the returns of a portfolio are bigger from the returns of a benchmark for T periods. For this reason, it is good news for the investor to have high value of success rate. It has the following formulation: $SR = \frac{1}{T}\sum_{t=1}^{T} I_t$, where $I_t = \begin{cases} 0 \text{ if } r_t \leq r_{b,t} \\ 1 \text{ otherwise} \end{cases}$ is the index of success, r_{it} is the monthly return of hedge fund i at time t and $r_{b,t}$ is the return of the benchmark at time t.

A frequently used risk-adjusted performance measure for mutual funds and for hedge funds is the Sharpe ratio developed by Sharpe (1996). The wide use of the Sharpe ratio (SR) may be attributed to its simplicity and ease of use. It measures the amount of excess return per unit of volatility. It is calculated by the formula: $SR = \left(R_p - R_f\right)/\sigma_p$, where R_p denotes the return of the hedge fund, R_f measures the risk free rate and σ_p the volatility of the hedge funds return. Graphically, in a mean-variance space, the Sharpe ratio is the slope of the line joining the risk-free asset to the hedge fund being examined. The Sharpe ratio is a benchmark free performance measure. The higher the Sharpe ratio, the better the hedge funds performance.

The information ratio (IR) for T periods is given by the following expression: $IR = \sum_{t=1}^{T} r_{dif,t} \Big/ stdev\left(r_{dif,t}\right)$, where $r_{dif,t} = r_{i,t} - r_{b,t}$ is the difference between the returns of portfolio P and the returns of the benchmark at time t. The higher information ratio, the better the hedge funds performance.

The estimation procedure for semi-deviation is similar to that for the standard deviation except we consider the deviation from the mean only when it is negative. Analytically, it can be formulated as follows: $\text{Semi-deviation}_i = \sqrt{\sum_{i=1}^{k} L_{it}^2}$, where $L_{it} = r_{it}$ if $r_{it} < 0$ and $L_{it} = 0$ if $r_{it} \geq 0$. r_{it} is the monthly return for the ith fund return in month t. The cutoff point of zero is obvious because returns below zero represent losses. The semi-deviation is more useful than the standard deviation when the underlying distribution of returns is skewed and just as useful when the underlying distribution is symmetric.

Looking at table 7.21, we conclude that the four factor GARCH(1,1) model, which include the factor mimicking portfolio for size and for book-to-market equity as well as the momentum factor, has the highest value of mean return (0.0131), annualized return (0.1578), cumulative return (0.3155), success rate (0.625), information ratio (4.3701) and the second highest value of Sharpe ratio (0.2603). Furthermore, this model gives riskier results than the other models, because it has the highest value of standard deviation (0.0505) and semi-deviation (0.153).

On the other hand, the multifactor GARCH(1,1) models, which have arisen by using the backward selection approach, gives the highest value of Sharpe ratio (0.3517) and the smallest value of standard deviation (0.0231) and semi-deviation (0.0655) than the other models.

CHAPTER EIGHT

CONCLUSION

The spectacular growth of hedge funds in recent years has prompted a significant increase in the number of studies that measure their performance and examine the sources of returns for various hedge fund strategies. As we have described in chapter four, there are many methodologies that researchers can follow in order to evaluate the performance of hedge funds and the persistence of this performance.

In our study, we evaluated performance of hedge funds in order to construct top decile portfolios. Totally, we used the monthly returns of ten hedge funds and the monthly returns of fourteen market indices. We applied four different factor models for each hedge fund and we constructed four different portfolios. We also applied the Generalized Autoregressive Conditional Heteroskedasticity GARCH(1,1) models in order to identify a suitable set of market indices for each hedge fund. Therefore, we constructed another four portfolios. Using some measures of risk, we concluded that GARCH(1,1) models tended to give better results than the rest of factor models.

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