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ΠΡΟΓΡΑΜΜΑ ΜΕΤΑΠΤΥΧΙΑΚΩΝ ΣΠΟΥΔΩΝ

EXPLORING HEDGE FUND PERFORMANCE DURING THE RECENT GLOBAL FINANCIAL CRISIS

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Μεταπτυχιακού Διπλώματος Ειδίκευσης.

Αθήνα,
Ιούλιος 2013

Εγκρίνουμε την εργασία της Τσαρουχά Ουρανίας

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Ιούλιος 2013

ΒΕΒΑΙΩΣΗ ΕΚΠΟΝΗΣΗΣ ΔΙΠΛΩΜΑΤΙΚΗΣ ΕΡΓΑΣΙΑΣ

«Δηλώνω υπεύθυνα ότι η συγκεκριμένη πτυχιακή εργασία για τη λήψη του Μεταπτυχιακού Διπλώματος Ειδίκευσης στη Λογιστική και Χρηματοοικονομική έχει συγγραφεί από εμένα προσωπικά και δεν έχει υποβληθεί ούτε έχει εγκριθεί στο πλαίσιο κάποιου άλλου μεταπτυχιακού ή προπτυχιακού τίτλου σπουδών, στην Ελλάδα ή στο εξωτερικό. Η εργασία αυτή έχοντας εκπονηθεί από εμένα, αντιπροσωπεύει τις προσωπικές μου απόψεις επί του θέματος. Οι πηγές στις οποίες ανέτρεξα για την εκπόνηση της συγκεκριμένης διπλωματικής αναφέρονται στο σύνολό τους, δίνοντας πλήρεις αναφορές στους συγγραφείς, συμπεριλαμβανομένων και των πηγών που ενδεχομένως χρησιμοποιήθηκαν από το διαδίκτυο».

Τσαρουχά Ουρανία ………………………………………

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Περίληψη

Η παρούσα διπλωματική εργασία πραγματεύεται το θέμα της απόδοσης των hedge funds τόσο στην περίπτωση που θεωρούνται ως μια μεμονωμένη επενδυτική επιλογή όσο και στην περίπτωση που συμμετέχουν σε ένα χαρτοφυλάκιο που περιλαμβάνει μετοχές και ομόλογα. Τα hedge funds αποτελούν, θεωρητικά τουλάχιστον, ένα ιδιαιτέρως επιθυμητό περιουσιακό στοιχείο από τους επενδυτές καθώς στοχεύουν σε υψηλές αποδόσεις μέσα από την αξιοποίηση επενδυτικών ευκαιριών διαφυλάσσοντας παράλληλα, το αρχικό κεφάλαιο από μια πιθανή οικονομική απώλεια. Για αυτό το λόγο, τα hedge funds γνώρισαν υψηλούς ρυθμούς ανάπτυξης μέχρι και το πρόσφατο παρελθόν. Αντίθετα, κατά την περίοδο της πρόσφατης παγκόσμιας οικονομικής κρίσης τα αποτελέσματά τους ήταν επιεικώς απογοητευτικά για τους επενδυτές. Στόχος, λοιπόν, αυτής της εργασίας είναι να διερευνήσει την απόδοση των hedge funds λαμβάνοντας υπόψη συγκεκριμένα χαρακτηριστικά τους όπως η αυτοσυσχέτιση που εμφανίζουν οι αποδόσεις τους, το πρόβλημα των υπερτιμημένων αποδόσεων που εμφανίζονται στις διαθέσιμες βάσεις δεδομένων καθώς διαγράφονται κεφάλαια χαμηλών αποδόσεων που σταμάτησαν να λειτουργούν και το γεγονός ότι δεν ακολουθούν την κανονική κατανομή.

Αρχικά, παρουσιάζονται τα κύρια ευρήματα της υπάρχουσας βιβλιογραφίας. Συγκεκριμένα, σε έναν αρκετά μεγάλο αριθμό μελετών ως μέτρα της απόδοσης των hedge funds χρησιμοποιούνται τα Sharpe Ratio και Jensen’s Alpha τα οποία βασίζονται στο Υπόδειγμα Αποτίμησης Περιουσιακών Στοιχείων και για αυτό το λόγο αγνοούν τα προαναφερθέντα χαρακτηριστικά των hedge funds. Από την άλλη πλευρά, υπάρχουν έρευνες όπου προτείνονται εναλλακτικά εργαλεία μέτρησης της απόδοσης των hedge funds τα οποία λαμβάνουν υπόψη τα χαρακτηριστικά της αυτοσυσχέτισης, των υπερτιμημένων αποδόσεων και της μη-κανονικότητας των αποδόσεων.

Στη συνέχεια, διεξάγεται μια λεπτομερής βιβλιογραφική έρευνα με σκοπό να προσδιοριστεί η πηγή από όπου θα αντλήσουμε τα δεδομένα μας. Βασιζόμενοι στα ευρήματα αυτής της έρευνας, καταλήγουμε στο συμπέρασμα ότι θα χρησιμοποιήσουμε τους δείκτες της Dow Jones Credit Suisse Hedge Fund Database. Επιπλέον, κρίσιμης σημασίας στην ανάλυση μας ήταν το γεγονός ότι έπρεπε να οριοθετήσουμε σε συγκεκριμένα χρονικά διαστήματα την περίοδο της κρίσης. Συνδυάζοντας τα αποτελέσματα από την εφαρμογή στατιστικών μεθόδων, όπως η

Recursive Least Squares method και το Chow Test, και τις πληροφορίες της σχετικής βιβλιογραφίας, εκτιμούμε ότι η περίοδος της πρόσφατης οικονομικής κρίσης ξεκίνησε το Φεβρουάριο του 2007 και συνέχισε να υφίσταται μέχρι και το Μάιο του 2009. Θέτοντας ως σημείο αναφοράς την περίοδο της οικονομικής κρίσης, μελετάμε την απόδοση των hedge funds σε ισοδύναμα χρονικά διαστήματα πριν και μετά την οικονομική κρίση με σκοπό τη συγκριτική ανάλυση των αποτελεσμάτων υπό διαφορετικές συνθήκες στην αγορά.

Ως αρχικό μέτρο της απόδοσης των hedge funds χρησιμοποιείται το Sharpe Ratio. Όμως, τα αποτελέσματα αυτού του δείκτη δεν είναι αξιόπιστα όταν υφίστανται τα προαναφερθέντα προβλήματα. Για αυτό το λόγο, λοιπόν, ελέγχουμε εάν το δείγμα μας υπόκειται σε αυτά τα προβλήματα. Επειδή αποδεικνύεται ότι ο συνδυασμός αυτών των τριών προβλημάτων πράγματι λαμβάνει χώρα στα δεδομένα όλων των υπο εξέταση χρονικών περιόδων, χρησιμοποιούμε το Adjusted Modified Sharpe Ratio το οποίο εκτιμάται ενσωματώνοντας τις “διορθωμένες” αποδόσεις και το Modified Value at Risk, το οποίο χρησιμοποιεί τη “διορθωμένη” για την αυτοσυσχέτιση τυπική απόκλιση και την τιμή z που λαμβάνει υπόψη την κύρτωση και την ασυμμετρία, την επονομαζόμενη Cornish-Fisher expansion.

Επιπρόσθετα, χρησιμοποιούμε την κλασσική μέθοδο βελτιστοποίησης χαρτοφυλακίου έτσι ώστε να προσδιορίσουμε το ποσοστό με το οποίο συμμετέχει το κάθε περιουσιακό στοιχείο στο χαρτοφυλάκιο που επιθυμούμε να διαμορφώσουμε. Για κάθε υποπερίοδο, σχηματίζουμε ένα χαρτοφυλάκιο που περιέχει μόνο ομόλογα και μετοχές και ένα χαρτοφυλάκιο που επιπλέον περιέχει hedge funds. Αυτά τα χαρτοφυλάκια συγκρίνονται με βάση το value at risk, το οποίο ουσιαστικά αντιπροσωπεύει την κλασσική προσέγγιση του Markowitz, και το adjusted modified value at risk του χαρτοφυλακίου, το οποίο ενσωματώνει τα προβλήματα της αυτοσυσχέτισης, των υπερτιμημένων αποδόσεων και της μη-κανονικότητας.

Εν κατακλείδι, παρατίθεται μια σύνοψη των αποτελεσμάτων που παράγονται από την παρούσα διπλωματική εργασία.

Executive Summary

Hedge funds constitute an asset class that aims at absolute returns by simultaneously exploiting investment opportunities and protecting principal from potential financial loss. For this reason, over the years, hedge funds became an exceptionally attractive investment tool and the hedge fund industry experienced tremendous growth rates. However, hedge fund performance figures during the recent global financial crisis were undoubtedly disappointing for investors. This thesis aims to shed more light on this issue by investigating hedge fund performance under a modified risk-adjusted framework that accounts for three important characteristics of hedge funds: the existence of autocorrelation, bias and fat tails.

First of all, a detailed overview of the existing literature is presented in reference to hedge fund performance measurement tools and the methods that are used for portfolio evaluation. There are numerous studies that investigate hedge fund performance employing classical performance measures such as the Sharpe Ratio and Jensen's Alpha which are rooted on the Capital Asset Pricing Model and thus, neglect the aforementioned characteristics of hedge funds. Additionally, many researchers use Modern Portfolio theory for the evaluation of a portfolio that contains traditional assets and hedge funds. The classical Markowitz approach is also considered inadequate for the evaluation of this portfolio. On the other hand, there is also extensive literature on alternative performance measurement tools that account for autocorrelation, bias and fat tails problems. Similarly, this thesis studies the combined effect of these problems on hedge fund performance.

A thorough investigation is initially conducted in order to identify the source of our data. Based on this research, we decide to use the hedge fund indices of the Dow Jones Credit Suisse Hedge Fund Database. Furthermore, a key step in our analysis is to bracket the financial crisis into specific time bounds. Through the synthetic analysis of statistical tests (Recursive Least Squares method, Chow Test) and apposite literature, we reach the conclusion that the financial crisis began around February 2007 and continued until May 2009. Apart from the crisis period, we also study two equal time intervals before and after the financial crisis in order to compare our results in different market conditions.

Specifically, hedge fund performance is firstly measured by the Sharpe Ratio for all the subperiods under examination. Afterwards, we investigate the existence of autocorrelation, bias and fat tails in our data sample. Furthermore, the Adjusted Modified Sharpe Ratio is estimated and its results are compared with those of the Sharpe Ratio. The Adjusted Modified Sharpe Ratio accounts for all the aforementioned problems as this measure is estimated incorporating the bias adjusted returns and the Modified Value at Risk, that uses the asset class adjusted for autocorrelation standard deviation and the Cornish-Fisher expansion which takes into consideration skewness and kurtosis.

Furthermore, we use a minimum variance optimization so that we can select the weights of the assets that form our portfolio. For each subperiod, we form a portfolio of traditional assets only and a portfolio that also contains hedge funds. These portfolios are compared on the basis of the portfolio value at risk, which actually represents the classical Markowitz approach, and the portfolio adjusted modified value at risk, which integrates autocorrelation, bias and fat-tails problems.

Finally, we submit a summary of conclusions, derived from the present work.

CHAPTER 1

Introduction

In general, the field of alternative investments constitutes an interesting area for research and analysis. The changing investment environment and the beneficial characteristics of alternative investments are responsible for the considerable growth of alternative investments in recent years. The attractiveness of alternative investments is reinforced by the heightened volatility in equity markets and low bond yields. Therefore many institutional investors and high-net worth individual investors turn their attention to alternative asset classes such as hedge funds, managed futures, private equity and real estate. Additionally, alternative investments provide investors with several potential investment advantages such as diversification, risk reduction, higher returns and capital preservation in volatile markets.

For the purposes of this master thesis, we will focus specifically on hedge funds. In literature, the term “hedge fund” is defined as an investment fund that includes a multitude of skill-based investment strategies with a broad range of risk and return objectives. A common element is the use of investment and risk management skills to seek positive returns regardless of market direction. The hedge fund market has demonstrated tremendous growth over the 1990’s. According to Anson (2002) the amount invested in this market has grown from an estimated $50 billion in 1990 to $362 billion in 1999. The 2000s were characterized by the institutionalization of the hedge fund industry. In this period, from the end of 1999 to the end of 2007, hedge funds’ assets quadrupled from $456 billion to $1,868 billion and continued to rise going into 2008[1]. However, disaster struck in 2008 and hedge fund strategies have underperformed the market since the end of 2010.

Tentatively, the conclusion is that the effectiveness of hedge fund strategies is questionable. Consequently, the purpose of this thesis is twofold. Firstly, we aim to extract conclusions on hedge fund performance as individual assets. Secondly, we will focus on whether or not the inclusion of hedge fund investment strategies contributed to the construction of efficient portfolios during the recent global financial crisis. The after effects of this financial crisis have

[1] Source: http://www.aima.org/en/education/aimas-roadmap-to-hedge-funds.cfm

not yet been fully measured and understood. Therefore the subject of this work constitutes an interesting field of research.

1.1 Thesis Objectives

The objectives of this thesis are:

i) Analyze the effect of financial crisis on hedge fund performance. Different subperiods are considered in order to emphasize on the impact of the recent profound financial distress on hedge funds both as standalone investment assets and as part of a portfolio.

ii) Examine whether or not classic performance measures, such as the Sharpe Ratio, which take into account the first two moments of a return distribution, that is mean and standard deviation, constitute adequate measures to evaluate the performance of hedge fund investment strategies.

iii) Employ performance measures which take into consideration higher order statistical moments, namely skewness and kurtosis, in order to better capture hedge fund characteristics.

iv) Compare hedge fund investment strategies to both stocks and bonds.

v) Investigate whether or not the inclusion of hedge funds adds value to the portfolio of an investor by displaying a beneficial effect of diversification. Specifically, one of the main objectives is to examine hedge fund correlations with traditional assets.

CHAPTER 2

Literature Review

Since the tremendous growth of hedge funds market over the 1990's, many efforts have been made to investigate the various aspects of the industry. This has proven to be an onerous task for two main reasons. Firstly, the available data on hedge funds should be corrected for various types of errors, autocorrelation, bias and fat tails. Secondly, tools like mean-variance analysis and the Sharpe ratio are no longer appropriate when hedge funds are involved. The combined effect of these issues should be taken into consideration in order to make a definite trade-off between profit and loss potential in the case of hedge funds.

In literature, there have been many studies evaluating hedge fund performance by classical performance measures such as the Sharpe Ratio, under which hedge funds provide a more efficient investment opportunity set for investors than traditional investment vehicles. Ackermann, McEnally and Ravenscraft (1999) analyze monthly return data for US and offshore funds and find that the average hedge fund Sharpe Ratio is higher than comparable mutual fund Sharpe Ratios. They confirm that the superior hedge fund performance over mutual funds is linked to incentive fees. Additionally, they conclude that hedge funds are able to outperform the market on a gross return basis but they are unable to consistently beat the market when absolute or total risk-adjusted returns are used. Liang (1998) compares hedge funds to mutual funds and confirms that hedge funds have higher Sharpe Ratios, higher abnormal returns, lower correlations and market betas than mutual funds. Brown, Goetzmann and Ibbotson (1999) examine the performance of the off-shore hedge fund industry over the period 1989 through 1995 and they find that offshore funds as a group have positive risk-adjusted performance when measured by Sharpe Ratios and by Jensen's alpha.

This paper is related to existing literature on the subject that hedge fund indices suffer from survivorship bias, autocorrelation and tail risk and therefore, exhibit significantly different performances. Fung and Hsieh (2002) suggest a simple solution that mitigates some of these biases and refers to an index based on the records of Fund of Funds (FOFs) which avoid many of the idiosyncratic biases in pro forma returns based on individual hedge funds extracted from databases. Asness, Krail and Liew (2001) state that the results of classical performance measures such as Sharpe Ratio are proved to be misleading due to the impact of survivorship bias, backfill bias and self-selection bias. Instead of examining simple Sharpe Ratios calculated using monthly returns, Asness, Krail and Liew suggest the method of the hedged Sharpe Ratios that take into account market exposure and the use of the lagged beta techniques that estimate more accurate betas. Lo (2001) examines several aspects of risk management for hedge funds, such as survivorship bias, dynamic risk analytics, liquidity and nonlinearities, and confirms that traditional risk management tools such as mean-variance analysis, beta and Value-at-Risk are unable to capture many of the risk exposures of hedge fund investments. Gregoriou (2004) points out that using the traditional Sharpe Ratio to rank hedge funds will underestimate the tail risk and overestimate performance. As a result, he suggests a superior tool for correctly measuring hedge fund risk-adjusted performance that is modified Sharpe Ratio and modified Value-at-Risk.

Ackermann, McEnally and Ravenscraft (1999) employ the methodology of Elton, Gruber and Rentzler (1987) for assessing the contribution of an alternative asset to an existing portfolio based on the Sharpe Ratio and the correlation of the new asset group and the existing portfolio. They reach the conclusion that hedge funds augment all of the bond and equity indices used in their survey. Amin and Kat (2003) discover that hedge funds present low levels of correlation with the S&P 500 and consequently, hedge funds are capable of producing an efficient payoff profile when mixed with the S&P 500. The inclusion of hedge funds in portfolios is also supported by the research paper of Gregoriou and Rouah (2002). Anson (2002) states that a Sharpe Ratio analysis cannot capture the impact of hedge fund non-linear payoffs and their exposure to event risk. Consequently, hedge funds cannot be examined within a mean-variance efficient frontier. For this reason, Anson includes skewness and kurtosis to his investigation. Kat (2003) constructs two portfolios with and without hedge funds and proves that when hedge funds are involved Markovitz Portfolio Theory is no longer appropriate due to the fact that the skewness and kurtosis of the portfolio return distribution is not taken into consideration. Favre and Galeano (2002) develop a methodology for portfolio optimization based on modified Value-at-Risk.

There have been many studies examining the autocorrelation problem, the bias problem and the fat-tail problem. Kat and Lu (2002) propose the method of unsmoothed returns (Geltner 1991, 1993) in order to deal with the problem that hedge fund returns exhibit positive first-order serial correlation. Getmansky, Lo, and Makarov (2004) derive mean, variance, Sharpe ratio, and beta formulae adjusted for serial correlation. Christiansen, Madsen and Christensen (2004) affirm that hedge funds present abnormal returns before correcting for survivorship bias. Agarwal and Naik (2004) find that the traditional mean-variance framework underestimates tail losses and to solve this problem they use the mean-conditional value-at-risk. Giamouridis and Vrontos (2005) suggest that the Regime Switching Dynamic Correlations model represents a more accurate tool for tail-risk measurement.

In this thesis, the approach employed to the strenuous problem of hedge fund performance measurement and portfolio optimization is based on a working paper by Eling (2005). The combined effect of the autocorrelation problem, the bias problem and the fat-tail problem is studied by Eling for the evaluation of hedge funds.

CHAPTER 3

Hedge Fund Data

3.1 The choice of database

Critical to the usefulness of the data and analysis in order to make an informed investment decision are the selection of an appropriate index and a full understanding of its built-in biases and limitations. The potential benefits of a hedge fund index for an investor initially refer to the strategic allocation process in a globally diversified portfolio. A hedge fund index provides information about the performance profiles of different strategies and a broadly representative picture of the composition, valuation and risks of the hedge fund industry over time, as well as its correlations with other asset classes. Hedge fund indices also offer the opportunity to measure the performance of hedge fund managers in a fair way based on the index returns. Additionally, an investor who seeks for controlled exposure to the asset class through a single, efficient, convenient investment without carrying specific risks can take advantage of a hedge fund index in order to construct an index-based, passive investment product. To gain this perspective, it is essential to understand how indices are constructed, the underlying methodologies utilized as well as the potential biases inherent in an index.

The construction flow of a hedge fund index begins with the hedge fund manager reporting the funds' description and performance to a hedge fund database. The hedge fund database provider aggregates the various funds that have reported and either gives hedge fund index providers access to its database or constructs indices itself. Typically, the database requires the hedge fund to describe its investments universe, terms and conditions and strategy/style. The index provider then assimilates the hedge fund database universe according to selection criteria which vary across index providers. At this stage, the index provider constructs an index with a new, condensed hedge fund universe that can be further broken down into sub-indices covering the variety of hedge fund strategies and styles[2].

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[2] Source:
http://www.pictet.com/en/home/investment_funds/pictet_alternative_investments/hedge_funds/hedge_funds_documentation.html

According to Lhabitant (2006) the key principles under which a hedge fund index should be constructed are:

- *Transparency*: The list of funds included in an index and the weight assigned to each fund should be fully disclosed and readily obtainable. The prices or returns used to compute the indices should also be available. The guidelines for altering the index, its components or their weights should be defined in advance and should be formed in a reasonable way.
- *Index coverage and representativity*: This subject raises the question of the index being comprehensive, namely the index should include as many funds as possible, versus being appropriate, that is to say exclude funds that a typical institutional investor would not want to hold.
- *Weighting*: An important question with hedge fund indices is whether the index should weight funds by market capitalization (i.e. assets under management) or assign an equal weight to all funds. In the traditional investment world, capitalization weighted indices constitute the decision of the weighting scheme. However, this decision is not always applicable in the case of hedge funds.
- *Investability*: From an investment perspective, a hedge fund index should represent the world of funds that are actually open to new investments and that can provide adequate capacity to absorb new investments for the foreseeable future. On the other hand, in terms of performance measurement, a hedge fund index should include closed funds as well. The investability policy of the index should be clearly specified, in any case.
- *Timely reporting*: It is necessary to obtain the index performance in a reasonable amount of time after the end of the month in question.
- *Stability of performance over time*: Once published, the performance of an index should not be revised retroactively.

These criteria are quite demanding, given the diversity and complexity of hedge fund industry, and as a result none of the indices constructed so far has gained universal acceptance. Apart from this, hedge fund indices are derived from the information included in databases of individual hedge funds. Many hedge funds release monthly return information to specialized databases such as Hedge Fund Research, CSFB (TASS)/Tremont, Barclays Hedge Fund and

CTA database, Hennessee and Morgan Style Capital Indices. The different way each database is constructed, i.e. net versus total fees, and the fact that data/prices are supplied by the hedge funds individually regarded, implying a considerable unreliability, constitute the two main reasons for hedge fund databases biases. It is important to analyze to some extent these biases that militate against an accurate representation of hedge fund strategies and as a result, distort performance.

- *Self-selection bias*: The hedge fund universe consists mainly of private structures and as consequence, reporting to a hedge fund database becomes completely voluntary. This leads to what is known as self-selection bias. In addition to this, hedge funds are not required to report performance to all databases. Figure 1 depicts that less than 1 per cent of the hedge fund industry reports to all databases, highlighting the unrepresentative nature of hedge fund databases.

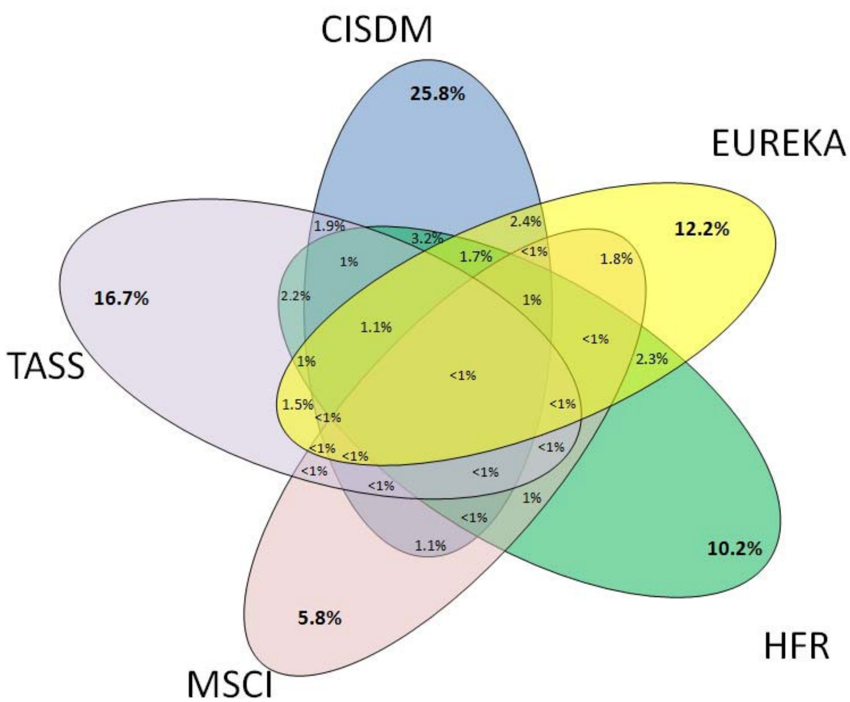

Figure 1: Industry coverage by hedge fund databases (Agrawal, Fos and Jiang, 2010)

- *Database/Sample Selection bias:* Another source of bias results from the selection of a database and a sample of hedge funds to work with. Different criteria used by the hedge funds managers also cause sample selection bias towards some segments of funds. The option of reporting to some databases and not to others implies discrepancy in the sample sets. Differences in data collection methods between databases are also other important source of sample selection bias (Ribeiro and Santos, 2011).

- *Survivorship bias*: Survivorship bias comes about when only surviving or operating funds are used to estimate the returns of a group of funds. This is likely to result in an upward bias because the omitted defunct funds generally have poorer performance than surviving funds (Fung and Hsieh, 2001).
- *Backfill bias*: Backfill bias or instant history bias occurs if database vendors backfill returns when a new fund is added instead of including its returns only on a going-forward basis. This will overstate index performance, since inclusion in the index is voluntary and thus funds will generally be added only after very good past performance (Asness, Krail and Liew, 2001).
- *Infrequent pricing and illiquidity bias*: Such bias occurs when hedge fund managers tend to smooth the returns and systematically understate portfolio's volatility and its correlations with traditional indices in order to overstate risk-adjusted returns (Lhabitant, 2006).

There is a variety of hedge fund index providers. Amenc and Martllini (2003), opine that there are three main providers of hedge fund indices:

1. *Evaluation Associates Capital Markets (EACM)*: EACM is an investment advisory firm that specializes in hedge funds and multi-manager investment programs for institutional and high net worth clients. Evaluation Associates Capital Markets offer one aggregate index, the EACM 100, as well as indices for five broad strategies and 13 underlying sub-strategies with data going back to 1990. EACM's indices are computed from an equally weighted composite of unaudited performance information provided by 100 private investment funds chosen by EACM. These funds are selected by EACM as being representative of their style and the index is rebalanced at the beginning of each calendar year. However, EACM does not disclose individual fund names or their weightings.
2. *Hedge Fund Research (HFR)*: Hedge Fund Research provides indices for seven strategies (convertible arbitrage, equity hedge, event-driven, merger arbitrage, distressed

securities), as well as an equally weighted aggregate index. The index was launched in 1994 with data going back to 1990 and currently there are more than 7000 funds included in HFR Database with new funds being added daily (www.hedgefundresearch.com). All HFRI indices are non-investable indices as they are constructed using both open and closed hedge funds, are equally weighted with respect to each fund and report monthly net of fees returns in USD. HFR has also published a series of HFRX indices which are constructed only of hedge funds that are open to investment, that is to say investable hedge fund indices.

3. *Dow Jones Credit Suisse Indices (formerly Credit Suisse First Boston/Tremont Indices (CSFB/Tremont)*: The DJ CS index was the industry's first and remains the leading asset-weighted hedge fund index. The DJ CS indices make use of the Credit Suisse Hedge Fund Database which tracks more than 8000 funds and cover nine strategies (convertible arbitrage, dedicated short bias, emerging markets, equity market neutral, event driven, fixed income arbitrage, global arbitrage, long/short equity and managed futures). The index was launched in 1999 with data going back to 1994 and only funds with audited financials are included. In August 2003, Dow Jones Credit Suisse also launched a series of investable indices based on a sample of 60 funds. In August 2003, the aggregate assets under management by the 60 investable index constituents were equal to approximately $55 billion, making it the industry's largest investable hedge fund index.

As already mentioned, the choice of an accurate database is of major interest in the context of the hedge fund industry, where a lack of transparency is often observed. Performance measurement, which is one of the main objectives of this thesis, based on an inaccurate database is biased in all cases. In literature, many studies gravitate towards the Dow Jones Credit Suisse and HFR hedge fund indices. The data on the working paper of Park and Staum (1998), who use the Treynor-Black appraisal ratio as performance measure, come from the Credit Suisse Hedge Fund Database. Agrawal and Naik (2000) measure hedge fund performance based on the methods of specific alpha and specific appraisal ratio and use data provided by the Hedge Fund Research (HFR) database. Kat and Menexe (2002) use the average risk-adjusted returns as hedge fund performance measure and the data in this study are taken from the Credit Suisse Hedge Fund Database. Baquero, ter Horst and Verbeek (2005) measure hedge fund performance based on relative risk-adjusted returns and they use data from the Credit Suisse Hedge Fund Database. Boyson (2003) uses data from Credit Suisse Hedge Fund Database and estimates alpha using a multi-factor model including style factors. De Souza and Gockan (2004) use data from the HFR database and average returns and Sharpe Ratio as performance measures.

It is important to be aware of the potential biases discussed above in evaluating the use of any hedge fund index as, for instance, some of these biases may have ambiguous effects on index returns. Liang (2000) examines survivorship bias in hedge fund returns by comparing two large databases, the HFR database and the Credit Suisse Hedge Fund Database. He reaches the conclusion that between the two databases, the Credit Suisse Hedge Fund Database is recommended for doing hedge fund research because of its relative completeness and accuracy. Additionally, Liang (2003) measures data accuracy and finds that the accuracy of the Credit Suisse Hedge Fund Database is consistent with his findings in Liang (2000) that the Credit Suisse Hedge Fund Database provides better data quality than Hedge Fund Research database. Asness, Krail and Liew (2001) support the opinion that the Credit Suisse Hedge Fund Database includes funds on a going-forward database only, and therefore, avoids any backfill bias. Furthermore, Anson (2009) compares the benefits of equally-weighted indices, such as HFR indices, and asset-weighted indices, such as DJ CS hedge fund indices. Specifically, Anson argues in favor of an asset weighted hedge fund index because, in this case, the full market impact from the hedge fund universe is more accurately reflected as an asset-weighted index conducts its transactions. In addition, it is better to use an asset-weighted index to compare against other asset classes that are benchmarked against capital-weighted indices, such as the S&P 500. Lhabitant (2006) also compares equally-weighted indices and asset-weighted indices and he finally suggests that asset-weighted indices effectively measure the performance of the average dollar invested in the industry, just as the S&P 500 measures the performance of the average dollar invested in the US stock market. Moreover, he states that equally weighted indices are less useful, unless one wants to measure the performance of the average manager in the industry.

Consequently, based on the findings of the literature previously discussed, the data that will be used in this thesis are the results of the Dow Jones Credit Suisse Hedge Fund Indices, taken from the Credit Suisse Hedge Fund Database.

3.2 Hedge fund Strategies

Hedge funds universe is very diverse and categorizing hedge funds is very difficult as there is a plethora of investment strategies with very different risk and return characteristics. There is no accepted norm to classify the different hedge fund strategies and each consultant, manager, investor or hedge fund data provider may design its own strategy classification or decide to use an external classification source. As already mentioned, the Dow Jones Credit Suisse Hedge Fund Indices will be employed for measuring hedge fund performance and as a result, it is useful to describe the classification suggested by the Credit Suisse Hedge Fund Database.

The methodology utilized in the Dow Jones Credit Suisse Hedge Fund Indices starts by defining the universe it is measuring. The index universe consists only of funds with a minimum of US $50 million assets under management, a minimum one-year track record and a current audited financial statement. Funds are separated into primary sub-categories based on their investment style. The Index in all cases represents at least 85% of the assets under management in the universe. The methodology analyzes the percentage of assets invested in each sub-category and selects funds for the Index based on those percentages, matching the shape of the Index to the shape of the universe.

The Credit Suisse Hedge Fund Database distinguishes fourteen different strategies which are explained thoroughly below[3]:

1. *Dow Jones Credit Suisse Convertible Arbitrage Hedge Fund*

This strategy typically aims to profit from the purchase of convertible securities and the subsequent shorting of the corresponding stock when there is a pricing error made in the conversion factor of the security. Managers of convertible arbitrage funds typically build long positions of convertible and other equity hybrid securities and then hedge the equity component of the long securities positions by shorting the underlying stock or options. Positions are designed to generate profits from the fixed-income security as well as the short sale of stock, while protecting principal from market moves.

[3] Source: https://www.credit-suisse.com/us/privatebanking/en/glossary_indices.jsp

2. *Down Jones Credit Suisse Dedicated Short Bias Hedge Fund*

Dedicated short bias funds typically take more short positions than long positions and earn returns by maintaining net short exposure in long and short equities. Short-biased managers take short positions mostly in equities and derivatives. Risk management often consists of offsetting long positions and stop-loss strategies.

3. *Dow Jones Credit Suisse Emerging Markets Hedge Fund*

Emerging markets funds typically invest in currencies, debt instruments, equities and other instruments of countries with "emerging" or developing markets (typically measured by GDP per capita). The index has a number of subsectors, including arbitrage, credit and event driven, fixed income bias, and equity bias.

4. *Dow Jones Credit Suisse Equity Market Neutral Hedge Fund*

Equity market neutral funds typically take both long and short positions in stocks while seeking to reduce exposure to the systematic risk of the market (i.e., a beta of zero is desired). Equity market neutral funds typically seek to exploit investment opportunities unique to a specific group of stocks, while maintaining a neutral exposure to broad groups of stocks defined for example by sector, industry, market capitalization, country, or region.

5. *Dow Jones Credit Suisse Event Driven Hedge Fund*

Event driven funds typically invest in various asset classes and seek to profit from potential mispricing of securities related to a specific corporate or market event. Event driven funds can invest in equities, fixed income instruments (investment grade, high yield, bank debt, convertible debt and distressed), options and various other derivatives.

6. *Dow Jones Credit Suisse Event Driven Distressed Hedge Fund*

These funds typically invest across the capital structure of companies subjected to financial or operational distress or bankruptcy proceedings. Such securities often trade at discounts to intrinsic value due to difficulties in assessing their proper value, lack of research coverage, or an inability of traditional investors to continue holding them. This strategy is generally long-biased in nature, but managers may take outright long, hedged or outright short positions. Distressed managers typically attempt to profit on the issuer's ability to improve its operation or the success of the bankruptcy process that ultimately leads to an exit strategy.

7. Dow Jones Credit Suisse Event Driven Multi-Strategy Hedge Fund

Multi-strategy event driven managers typically invest in a combination of event driven equities and credit. Multi-strategy event driven managers typically have the flexibility to pursue event investing across different asset classes and take advantage of shifts in economic cycles.

8. Dow Jones Credit Suisse Event Driven Risk Arbitrage Hedge Fund

Risk arbitrage event driven hedge funds typically attempt to capture the spreads in merger or acquisition transactions involving public companies after the terms of the transaction have been announced. The spread is the difference between the transaction bid and the trading price.

9. Dow Jones Credit Suisse Fixed Income Arbitrage Hedge Fund

Fixed income arbitrage funds typically attempt to generate profits by exploiting inefficiencies and price anomalies between related fixed income securities. Funds often seek to limit volatility by hedging out exposure to the market and interest rate risk. Strategies may include leveraging long and short positions in similar fixed income securities that are related either mathematically or economically.

10. Dow Jones Credit Suisse Global Macro Hedge Fund

Global macro funds typically focus on identifying extreme price valuations and leverage is often applied on the anticipated price movements in equity, currency, interest rate and commodity markets. Managers typically employ a top-down global approach to concentrate on forecasting how political trends and global macroeconomic events affect the valuation of financial instruments. Profits can be made by correctly anticipating price movements in global markets and having the flexibility to use a broad investment mandate, with the ability to hold positions in practically any market with any instrument. These approaches may be systematic trend following models, or discretionary.

11. Dow Jones Credit Suisse Hedge Fund

The Dow Jones Credit Suisse Hedge Fund Index is compiled by Credit Suisse Hedge Index LLC and CME Group Index Services LLC. It is an asset-weighted hedge fund index comprising the performance of all strategies and includes only funds, as opposed to separate accounts. The index is calculated and rebalanced on a monthly basis, and reflects performance net of all hedge fund component performance fees and expenses.

12. Dow Jones Credit Suisse Long/Short Equity Hedge Fund

Long/short equity funds typically invest in both long and short sides of equity markets, generally focusing on diversifying or hedging across particular sectors, regions or market capitalizations. Managers typically have the flexibility to shift from value to growth; small to medium to large capitalization stocks; and net long to net short. Managers can also trade equity futures and options as well as equity related securities and debt or build portfolios that are more concentrated than traditional long-only equity funds.

13. Dow Jones Credit Suisse Managed Futures Hedge Fund

Managed futures funds (often referred to as CTAs or Commodity Trading Advisors) typically focus on investing in listed bond, equity, commodity futures and currency markets, globally. Managers tend to employ systematic trading programs that largely rely upon historical price data and market trends. A significant amount of leverage may be employed since the strategy involves the use of futures contracts. CTAs tend not to have a particular bias towards being net long or net short any particular market.

14. Dow Jones Credit Suisse Multi-Strategy Hedge Fund

Multi-strategy funds typically are characterized by their ability to allocate capital based on perceived opportunities among several hedge fund strategies. Through the diversification of capital, managers seek to deliver consistently positive returns regardless of the directional movement in equity, interest rate or currency markets. The added diversification benefits may reduce the risk profile and help to smooth returns, reduce volatility and decrease asset-class and single-strategy risks.

These hedge fund indices can be further classified into broader classes as depicted to the following table[4]:

[4] Source: http://www.iam.uk.com/press/lse-publications/An-Introduction-to-Hedge-Fund-Strategies.pdf

Strategy Class	Specific Strategy/Index
Aggregated	
	Hedge Fund
Event Driven	*Hedge funds that follow this approach look for events that are expected to make an impact over a relatively short period of time.*
	Distressed Securities
	Risk Arbitrage
	Event Driven
	Event Driven Multi-Strategy
Relative Value	*These strategies are designed to take advantage of perceived mispricing among related financial assets.*
	Fixed Income Arbitrage
	Convertible Arbitrage
Long/Short	*These strategies exploit the ability of hedge fund managers to freely short equities.*
	Long/Short equity
	Dedicated short bias
	Equity Market Neutral
Tactical	*These strategies attempt to profit by forecasting the overall direction of the market or a market component.*
	Global Macro
	Managed Futures
Location	*Hedge funds can also be grouped according to the geographical location of the assets they trade in.*
	Emerging Markets
Multiple Strategy	*The hedge fund manager changes investment strategies depending on market conditions, or allocates capital across different strategies simultaneously.*
	Multi-strategy

Table 1: Categories of Dow Jones Credit Suisse Hedge Fund Indices

3.3 Subperiods identification

One of the main objectives of this thesis is to analyze the effect of the financial crisis on hedge fund performance. As a consequence, it is crucial to define specifically the period of financial crisis which is a rather difficult task. Even when a potential trigger is identified, in many cases this triggering event to which a crisis is attributed seems small relative to the crisis that follows. For the recent global financial crisis, the blame is usually laid on the subprime mortgage market that began to turn detrimental in late 2006. However, the subprime mortgage market constituted a small proportion, only about 4%, relative to the overall mortgage market, the crisis originated in the subprime mortgage market propagated across many sectors of the economy causing severe damage (Constantinides et al., 2013).

Fung and Hsieh (2004) study FoHF indices and perform a modified version of the cumulative sum tests in order to find structural break-points. They actually linked hedge fund returns with market events by looking for market events around the time of the statistical sample breaks achieving, based on this context, to pinpoint the time for the actual break. Edelman et al. (2012) present a financial model to document performance characteristics using a data set of funds of hedge funds from January 2005 to December 2010. Following Fung and Hsieh (2004) analysis, they identify structural break-points with major market events; namely, they divide their sample period in three subperiods: January 2005 to June 2007 (pre-subprime crisis), July 2007 (the beginning of the subprime crisis) to March 2009 (the turnaround after the end of the credit crisis) and April 2009 to December 2010 (post-credit crunch). Billio et al. (2010) analyze the impact of financial crisis on hedge fund risk and study their data during the 2007 subprime mortgage crisis (August 2007-January 2008) and the 2008 Global financial crisis (September 2008-November 2008). Xu et al. (2010) use monthly return data, namely active and inactive hedge funds, funds of funds and CTAs obtained from the Center for International Securities and Derivatives Markets (CISDM), from January 1994 to March 2009. They perform the Chow test which reveals that the subperiod from February 2007 to December 2008 corresponds to the global financial crisis. Schaud and Schmid (2012) use data from the TASS Database and their investigation period starts from January 1994 and ends in December 2008. They highlight the severity of the recent financial crisis for the hedge fund industry by underlying the fact that the number of funds leaving the database has never been as high as in the recent global financial crisis of 2007/2008. Xu et al. (2011) also note that hedge funds have not been subject to a financial crisis on the order of magnitude witnessed from 2007 through early 2009. Kaiser and Haberfelner (2011) explore how hedge fund database biases developed during the 2007-2009 financial crisis. Eling (2013) studies the performance of FoHFs with a time horizon from 1994 to 2011 which is subdivided into two different subperiods; the pre-crisis period that ranges from January 1994 to August 2008 and the post-crisis period that goes from September 2008 to December 2011.

Chart 1 depicts the compound annual rate of return (CARR) of HFRI Fund of Funds Composite Index during the period 1990-2012. It is evident that the drawdown began around 2007 and in 2008 the debacle occurred and was particularly harmful for the institutional investors as their overall hedge fund experience turned into a loss-making venture.[5]

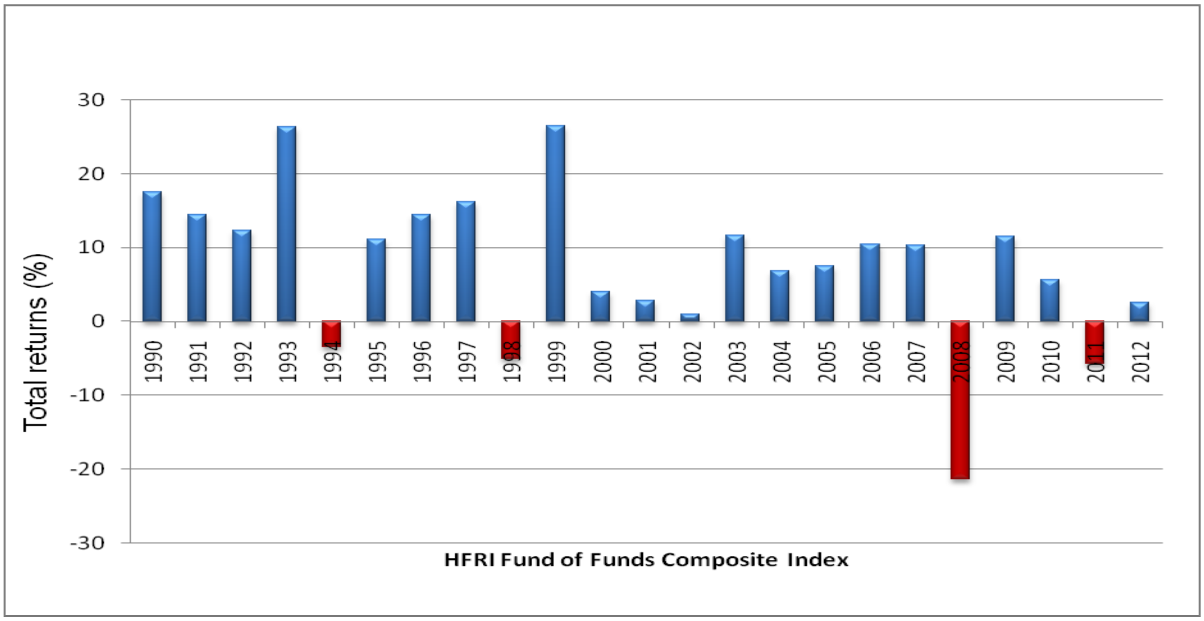

Chart 1: Compound annual rate of return (CARR) of HFRI Fund of Funds Composite Index

Additionally, it is remarkable that despite the quite significant performance in 2009, the compound annual rate of return (CARR) of HFRI Fund of Funds Composite Index noted a decreasing trend in the years 2010-2011.

Moreover, chart 2 shows the monthly logarithmic returns of DJ CS Hedge Fund Index from 2001 to 2012. It is not difficult to distinguish the values in the data set that are inconsistent with the main pattern of the data. The outlier values are:

- September, October and November 2008,
- May 2009,
- May 2010 and
- September 2011.

[5] Source: http://www.aima.org/download.cfm/docid/E9031A27-E978-4009-85EA1A8D325DAF7D

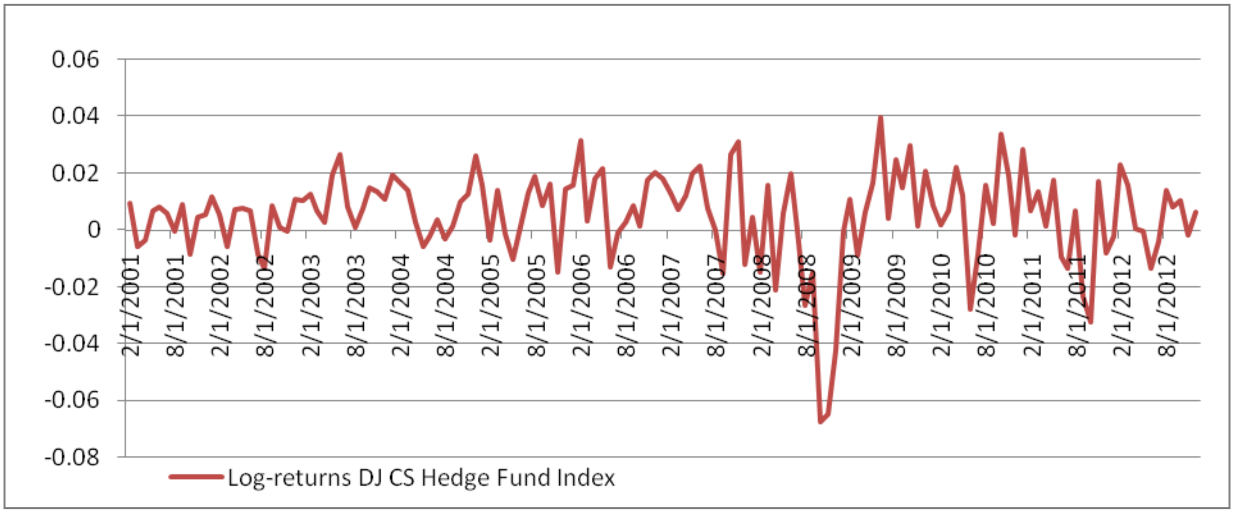

Chart 2: Monthly logarithmic returns of DJ CS Hedge Fund Index

Furthermore, market events can be distinguished by examining financial markets and real economy indicators. Mishkin (2001) affirms that most financial crises in the United States have begun with a stock market crash. In addition to this, Anson (2002) indicates that hedge funds invest in the same equity and fixed income securities as traditional long-only managers pursuing, though, alternative investment strategies. Consequently, in this case, the most obvious marker of a financial crisis is a downturn in equity markets. The United States stock market activity is studied by examining two benchmark indices; the S&P 500 index and the Dow Jones Industrial. It is evident from chart 3 and 4 that the economic downward spiral began around August 2007 and continued until May 2009 when the stock market began to follow an upward trend. The recovery seems to be really sluggish as the stock market activity approaches the pre-crisis levels around 2011.

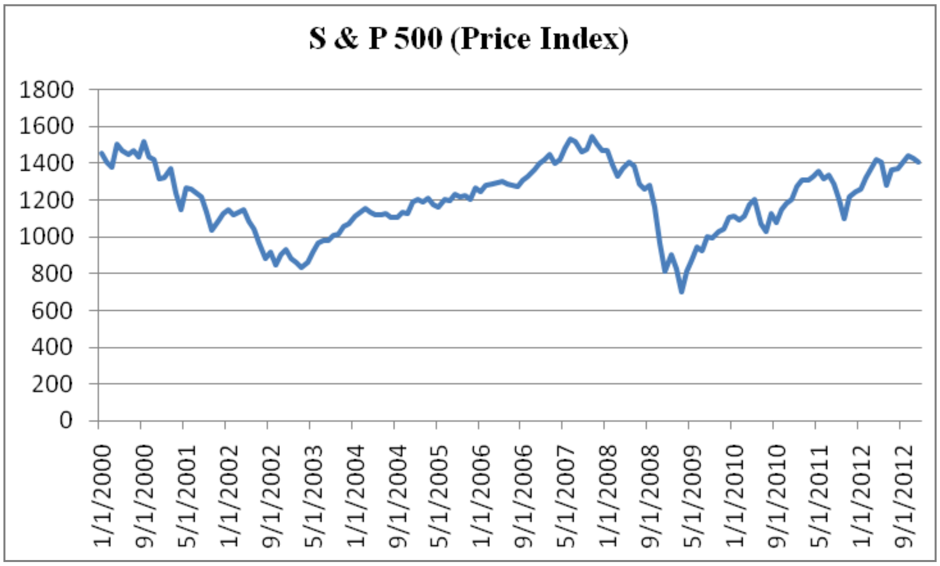

Chart 3: S&P 500 – Price Index

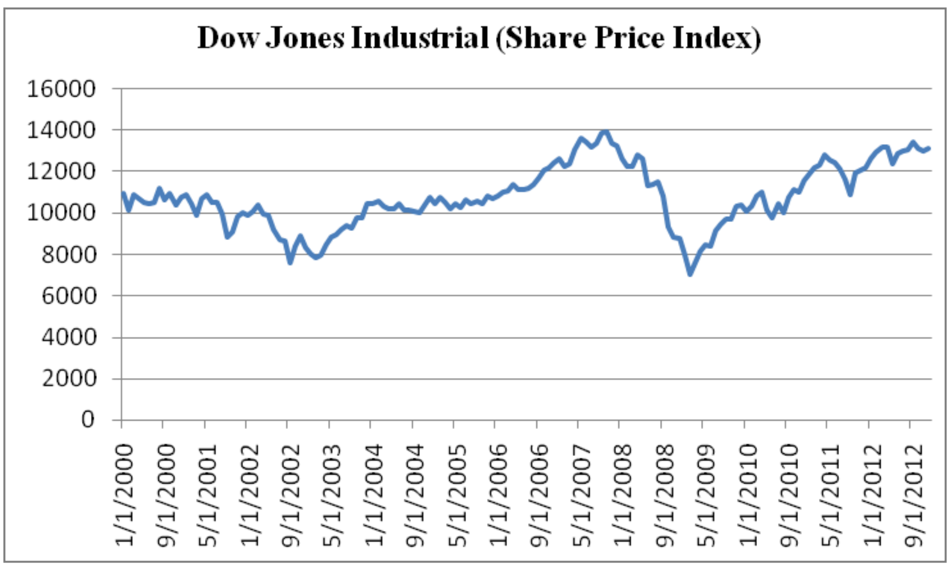

Chart 4: Dow Jones Industrial – Share Price Index

Khadani and Lo (2008) note that during the first half of 2007, the events in the U.S. sub-prime mortage markets caused the turmoil in both the stock market and the fixed-income world. In July 2007, the performance of certain well-known equity-valuation factors, such as Fama and French's Small-Minus-Big (SMB), market-cap and High-Minus-Low (HML) and Book-to Market factors, began a downward trend and in August 2007, some of the most successful equity hedge funds in the history of the industry reported record losses (Zuckerman et al., 2007; Sender et al., 2007). Finally, even though Khadani and Lo (2008) propose the August of 2007 as the beginning of the financial crisis, they underscore that other liquid investment categories such as global macro and managed futures seem to have experienced a similar downward trend earlier in 2007.

In order to define the structural break, the method of recursive least squares (RLS method) can be applied. Recursive estimation simply involves starting with a subsample of the data, estimating the regression, then sequentially adding one observation at a time and re-running the regression until the end of the sample is reached. The RLS method provides qualitative information which can be plotted and thus gives a visual impression of how stable the parameters appear to be. Two important stability tests are derived from the recursive residuals, the CUSUM (cumulative sum of the residuals) and the CUSUMSQ (cumulative sum of the squared residuals) stability tests that identify the statistical breakpoint (Brooks, 2008). The estimation regression used is based on Carhart's four factor model which in literature (Kapoor, 2012; Eling and Faust, 2010) is considered as a traditional performance measurement model. Carhart's four factor model focus primarily on stock market and therefore, it is selected for the identification of the recent global financial crisis. Formally,

$$R_{it} - R_{ft} = \alpha_i + \beta_{0i} (R_{mt} - R_{ft}) + \beta_{1i}SMB_t + \beta_{2i}HML_t + \beta_{3i}MOM_t + \varepsilon_{it} ,$$

where R_{it} is the return of Dow Jones Credit Suisse Hedge Fund Index, which is an aggregate index comprising the performance of all strategies, in month t, $R_{it} - R_{ft}$ is the excess fund return, $R_{mt} - R_{ft}$ is the value weighted excess return on the market portfolio, SMB is a size factor and computes the difference in return between a small cap portfolio and a large cap portfolio, HML is the difference in return between a portfolio of high book-to-market stocks and a portfolio of low book-to-market stocks, and MOM is the momentum factor which accounts for trend-following strategies in stock markets and computes the difference in return between a portfolio of past winners and a portfolio of past losers. The factors are downloaded from Kenneth R. French data library for the period 2000-2012[6].

Chart 5 depicts the results of the CUSUM test.

[6] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research

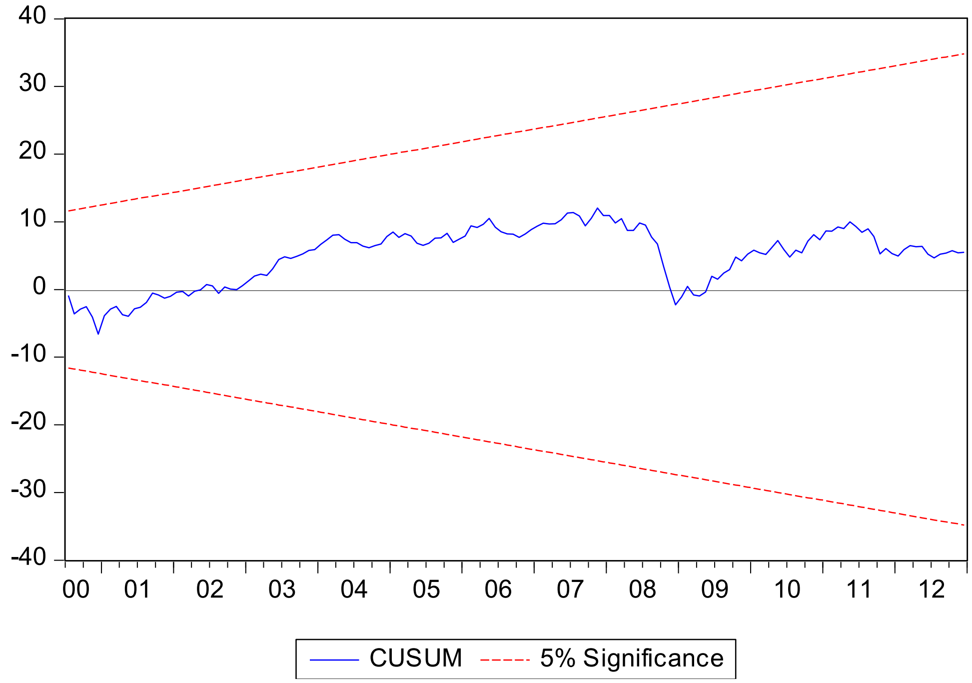

Chart 5: CUSUM test

Since the line is well within the confidence bands, the conclusion is that the null hypothesis of stability is not rejected. However, this result cannot be retained due to the fact that the plot of the CUSUMSQ test indicates that the parallel lines are crossed thus providing evidence of structural instability. Specifically, by employing the CUSUMSQ test, the structural breaks are evident to the following chart as the statistics lying outside the 95 percent confidence bands for the period from January 2007 to October 2008.

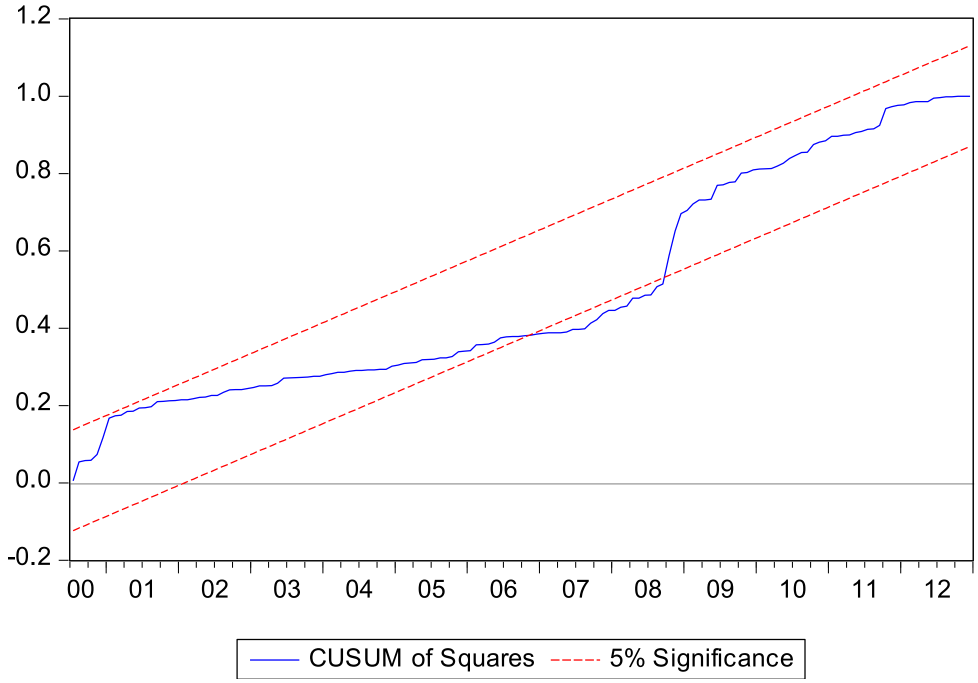

Chart 6: CUSUMSQ test

The stock market crash usually sets off a number of amplification mechanisms and, ultimately, this often leads to significant turbulences in economic activity. Real economy reacts later to the likelihood of a financial crisis than the stock market. Bustelo (2000) examines financial crises in the 1990s and finds that one of the leading indicators of financial debacles is the higher levels of unemployment rate. In order to examine this real economy indicator for the case of the United States, the data used are collected from the Datastream Database on a monthly basis for the period 2000-2012. The following chart depicts that the unemployment rates present an abrupt increase from 2008 to 2011 when a decreasing trend is noted.

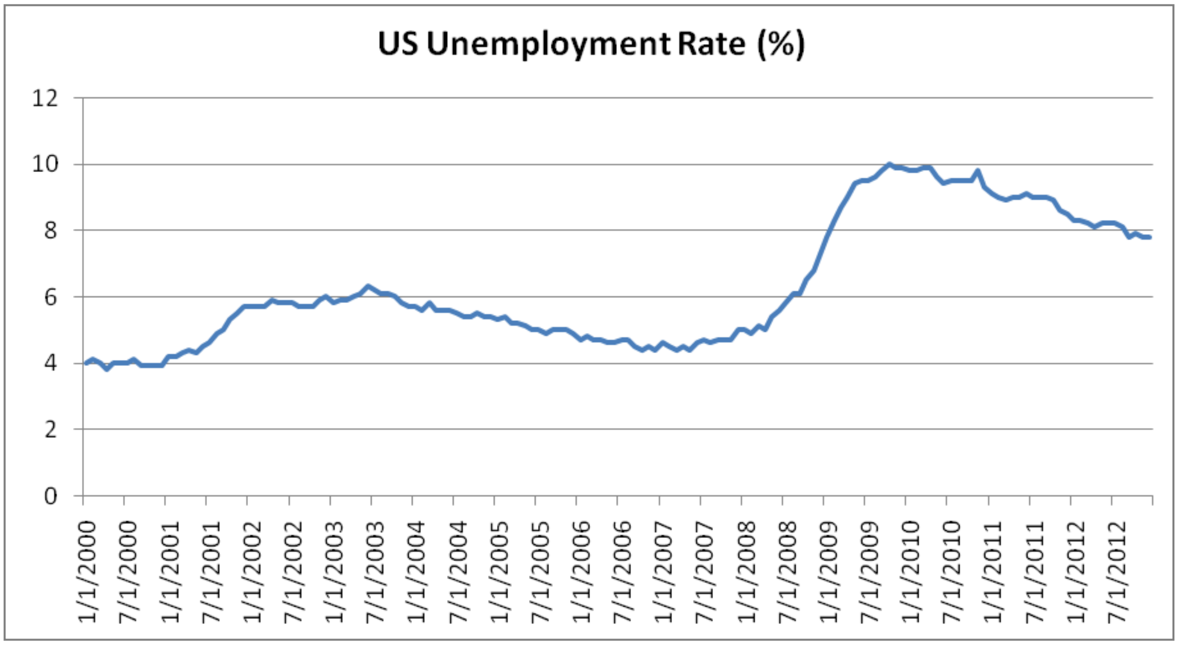

Chart 7: US Unemployment Rate

According to the empirical studies of Berg and Partillo (1999) and Bussiere and Mulder (1999) another important indicator of financial crises is considered to be the slowdown in real GDP growth. The chart of US GDP quarterly measurements indicates this deterioration in GDP from 2008 until the recovery year of 2010.

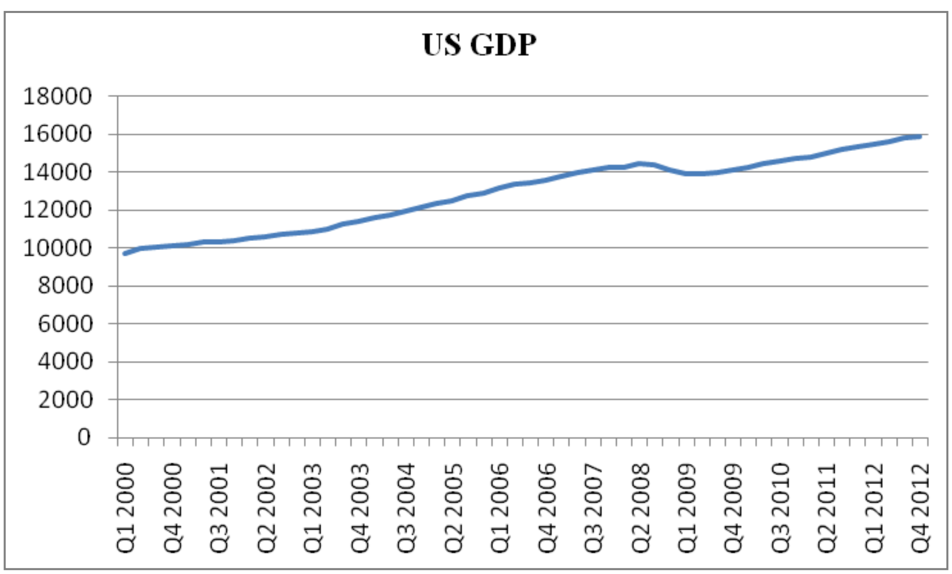

Chart 8: US GDP

Overall, it is obvious that there is a linkage between market events and hedge fund performance. Combining the results of previous analysis, the crisis phase can be defined from February 2007 to May 2009. Following Xu et al. (2010) hedge fund risk-based performance framework, a multi-factor model is applied in order to examine whether these structural breaks are evident in hedge fund performance as well. It consists of the five trend-following risk factors proposed by Fung and Hsieh (2001): PTFSBD, the return on the PTFS Bond Lookback straddle; PTFSFX, the return on the PTFS Currency Lookback Straddle; PTFSCOM; the return on the PTFS Commodity Lookback Straddle; PTFSIR, the return on the PTFS Short-term Interest Rate Lookback Straddle; and PTFSSTK, the return on the PTFS Stock Index Lookback Straddle[7]. It also includes five linear factors: the three Fama-French factors of the stock market excess return, the size factor, and the value factor, the change in the credit spread between the Baa corporate bonds and the ten-year Treasuries, and a term structure spread between the ten-year and three-month Treasuries[8]. The multi-factor model is estimated according to the following type:

$$R_{it} - R_{ft} = \alpha_i + \beta_{0i}\,(R_{mt} - R_{ft}) + \beta_{1i}SMB_t + \beta_{2i}HML_t + \beta_{3i}SPRD10Y3M + \beta_{4i}SPRDBAA10Y$$
$$+\beta_{5i}PTFSBD + \beta_{6i}PTFSCOM + \beta_{7i}PTFSFX + \beta_{8i}PTFSIR + \beta_{9i}PTFSSTK$$

Using monthly data of Dow Jones Credit Suisse Hedge Fund Index and conducting the Chow test to the multi-factor model we reach the conclusion that a structural breakpoint indeed occurred in February 2007 and marks the start of the global financial crisis. Table 2 presents this result of the Chow test and because all three test statistics are greater than their critical values, the null hypothesis that there are no breaks at the specified breakpoint is rejected.

Chow Breakpoint Test: 2007M02
Null Hypothesis: No breaks at specified breakpoints
Varying regressors: All equation variables
Equation Sample: 2000M02 2012M12

F-statistic	0.720266	Prob. F(11,133)	0.7175
Log likelihood ratio	8.968917	Prob. Chi-Square(11)	0.6248
Wald Statistic	7.922925	Prob. Chi-Square(11)	0.7202

Table 2: Chow Breakpoint Test – February 2007

[7] PTFS stands for Primitive Trend Following Strategies as defined in Fung and Hsieh (2001). Data are downloaded from: http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls

[8] Data on the Treasury yields and BAA corporate bond yields are obtained from the Federal Reserve website at: http://www.federalreserve.gov/releases/h15/data.htm

Similar results are deduced by entering May 2009 as a breakpoint (Table 3).

Chow Breakpoint Test: 2009M05			
Null Hypothesis: No breaks at specified breakpoints			
Varying regressors: All equation variables			
Equation Sample: 2000M02 2012M12			
F-statistic	0.961660	Prob. F(11,133)	0.4845
Log likelihood ratio	11.86232	Prob. Chi-Square(11)	0.3741
Wald Statistic	10.57826	Prob. Chi-Square(11)	0.4792

Table 3: Chow Breakpoint Test - May 2009

The crisis phase, though, cannot be examined in isolation and as a result, hedge funds performance is studied during three equivalent time periods. Specifically, the time horizon under examination can be defined from January 2005 to October 2011 and is subdivided into three different time intervals; the first one is settled from January 2005 to January 2007 (the pre-crisis period), the second from February 2007 to May 2009 (the credit crisis period) and June 2009 to October 2011 (the post-credit crisis period).

3.4 Data

The empirical investigation is based on the monthly returns of the Dow Jones Credit Suisse Hedge Fund Indices, which describe thirteen different hedge fund strategies and a fourteenth strategy reflected by the aggregated index comprising the performance of all the strategies considered, over the period from January 2005 to October 2011, as it is previously mentioned. The hedge fund indices are compared to broad based securities benchmarks. Specifically, Standard's & Poor's 500 (S&P 500), which is an index with a focus on the US capital market, and Morgan Stanley Capital International World (MSCI World), which is a world index, are used as equity performance measures. Additionally, for the bonds the indices used are Barclays US Aggregate Index which focuses on the US capital market and is considered representative of the US investment-grade, fixed-rate bond market and BofA Merill Lynch Global Government Bond Index which is a worldwide index and tracks the performance of government bonds.

The analysis focuses on US market and the world capital market. This selection is the result of the fact that the sub-prime crisis that erupted in the United States was the first manifestation of the largest financial crisis that has since swept across the world. Furthermore, hedge funds are mainly present in US market. According to Jobman (2002), about one-third of the funds and more than 90 percent of the fund managers are domiciled in the United States.

CHAPTER 4

Hedge Fund performance measurement

The financial crisis, when credit markets became illiquid, emphasized the importance and the complexities of valuing hedge funds. In the not so distant past, it was widely believed that hedge funds could offer investors a variety of diversification benefits and were able to generate returns better than conventional investment instruments. Hedge fund managers achieved these goals by employing a wide variety of strategies which include short selling, leveraging and complex derivatives that, in the context of a portfolio, aim to reduce exposure to volatile assets and introduce low or negative correlation into the mix.

A number of sophisticated measures have been developed to monitor the performance of hedge funds. Risk-adjusted performance measures can be divided into traditional performance measures, based on the mean-variance approach, and VaR-based measures. As far as the first category is concerned, the followng measurement tools can be included:

- *The Sharpe Ratio*: Devised by William Sharpe (1996). Its aim is to measure the amount of excess return per unit of volatility provided by a fund. It is calculated as follows:

$$SR_i = \frac{r_i - r_f}{\sigma_i}$$

where r_i represents the return on a fund, r_f is the risk-free rate and σ_i is the standard deviation of the fund. A high and positive Sharpe ratio shows a firm's superior risk-adjusted performance, while a low and negative ratio is an indication of unfavorable performance.

- *The Treynor Ratio*: In a sense, the Treynor Ratio is a reward-to-risk ratio similar to the Sharpe Ratio. The key difference is that it looks at systematic risk (beta) only, not total risk (standard deviation). Algebraically:

$$TR_i = \frac{r_i - r_f}{\beta_i}$$

where r_i represents the return on a fund, r_f is the risk-free rate and β_i is the beta of the fund.

- *Jensen's Alpha*: Jensen's alpha was introduced in Jensen (1968) and equals the intercept of the regression,

$$\mathbf{r_i\text{-}r_f = \alpha + \beta_i\,(r_M\text{-}r_f) + e_h,}$$

where r_i is the fund return, r_f is the risk-free rate and r_M is the total return on the market index.

Continuing to the second category of hedge funds performance measurements, one of the most popular measures of financial risk is Value-at-Risk (VaR). Value at Risk is defined as the expected maximum loss over a chosen time horizon within a given confidence interval, that is: P(loss > VaR) ≤ 1-α, where α is the confidence level, typically 0.95 and 0.99. There is a number of different approaches to VaR, two of them are presented below (Favre and Galeano (2002)):

- *Normal VaR*: Traditional calculation of normal VaR assumes that the portfolio's rate of return is normally distributed, which means that the distribution of returns is perfectly described by their mean and standard deviation. It uses normal standard deviation and looks at the tail of the distribution. In general, the value at risk for a confidence level α is:

$$\mathbf{VaR_i = -(z_\alpha \sigma_i + r_i)w,}$$

where z_α is the quantile of the standard normal distribution and w denotes the value of the investment.

- *Modified VaR*: This measure takes into account third and fourth order moments of the return distribution. It uses the Cornish-Fisher (1937) expansion to compute Value-at-Risk analytically. Normal VaR is adjusted with the skewness and kurtosis of the distribution:

$$\mathbf{z_{CF} = z_C + \frac{1}{6}(z_C{}^2 - 1)S + \frac{1}{24}(z_C{}^3 - 3z)K - \frac{1}{36}(2z_C{}^3 - 5z_C)S^2,}$$

where z_C is the critical value for probability (1-α), S is the skewness and K the excess of kurtosis. The modified VaR is then:

$$\mathbf{MVaR_i = -(z_{CF}\sigma_i + r_i)w.}$$

On the whole, both the Treynor ratio and Jensen's alpha issue from the CAPM and measure risk the same way. On the one hand, the fact that the Sharpe ratio focuses on non systematic risk while the Treynor Ratio on systematic risk leads to the result that Sharpe Ratio penalizes funds that that have a high volatility and in the case of hedge funds this is important because the non-systematic component is usually large (Lhabitant, 2006). On the other hand, some researchers (Agarwal, 2000) imply that alpha is an inappropriate measure of hedge funds performance on the grounds that hedge funds tend to be not normally distributed. In addition to this, Eling and Schuhmacher (2007) conclude that both from a theoretical and a practitioner's point of view Sharpe ratio is the proper metric for hedge fund performance analysis. As a consequence, in this thesis, the Sharpe Ratio is used as classic risk-adjusted performance measure.

4.1 Classic performance measurement

Condensing return and risk into one useful risk-adjusted number is one of the key tasks of performance measurement. When it is correctly done, the estimation and evaluation of the expected risk-return trades-offs for the alternative investments available become possible. This aspect is of fundamental importance to investors because it defines the investment decisions process. In this section, hedge fund performance is examined by using the Sharpe Ratio which is undoubtedly the most commonly used measure of risk-adjusted performance. According to Dorfleitner (2003), the term return should always be defined explicitly at the beginning of an empirical work. In literature, the decision of computing arithmetic or geometric averages as well as discrete or continuously compounded returns is a controversial task. In this case, the arithmetic mean of discrete returns is used. Ibboston and Sinquefield (1979) conclude that the arithmetic mean is a better measure of a portfolio's return and serves as a better representation of typical performance over single periods than the geometric mean. Furthermore, Dorfleitner (2003) states that discrete returns are to be used whenever portfolio aspects are the topic of interest while continuously compounded returns are suited for time series models such as GARCH models due to their property of time additivity.

Consequently, the discrete returns $r_{t1,t2}$ of a fund between any time t_1 and $t_2 \geq t_1$ are defined as

$$\mathbf{r}_{t_1,t_2} = \frac{\mathbf{NAV}_{t_2} - \mathbf{NAV}_{t_1}}{\mathbf{NAV}_{t_1}}$$

The net asset value (NAV) at time t of a given hedge fund, with the index t representing any point in time, is based upon the aggregated performance of the constituent hedge fund managers within the specific hedge fund index; post the fees and expenses of the fund of fund platform.

The discrete returns are calculated similarly for equity and bond indices. The arithmetic average monthly return for security i, r_i, is computed simply by summing the return in each sub-period and dividing the total by the number of sub-periods T. The arithmetic mean of discrete returns is used as input to the Sharpe Ratio.

The risk-free rate is different for the three different time intervals under examination. Government security rates are usually used as risk-free rates but it is crucial to take into consideration the fact that there are differences on whether to use short term or long term rates. Damodaran (2008) states that during market crises, it is common to see big differences between short term and long term rates in either direction; that is to say whether the yield curve is downward sloping indicating that short term rates are much higher than long term rates or the yield curve is excessively upward sloping with long term rates exceeding short term rates by more than 2%. For instance, the long term 10-year Treasury bonds present an annual rate of 2.95% whereas the short term 3-month Treasury bill rates are equal to 0.11% during 2009 which is considered to be the peak of the financial crisis. On the other hand, during 2006 the long term 10-year Treasury bonds have an annual rate of 4.58% while the short term 3-month Treasury bills present an annual rate of 4.08%. Consequently, it is obvious that the choice between long term and short term rates will have significant impact on the results of performance measurements because it will lead either to an overestimated or an underestimated hedge fund performance. Travers (2004) employs as risk-free rate the 90-day T-bills rate commenting that it is the typically used proxy. In addition to this, Lhabitant (2006) states that the risk-free asset is often specified as Treasury bills. Accordingly, the three-month Treasury bill rates are used as the risk-free asset[9]. For the pre-crisis period from January 2005 to January 2007 the average yield per annum is calculated to be 4.074%, namely 0.34% per month. Moreover, for the credit crisis period which is settled from February 2007 to May 2009 the average yield per annum is calculated to be 2.37%, namely 0.19% per month. Finally, for the post-credit crisis period from June 2009 to October 2011 the average yield per annum is calculated to be 0.10%, namely 0.009% per month.

The performance measurement results on the basis of the Sharpe Ratio are shown in tables 4, 5 and 6.

[9] The data for the three-month Treasury bill rates are taken from: http://www.forecasts.org/data/data/GS3M.htm

Specific Strategy/Index	Mean Monthly Return in % (r_i)	Standard Deviation of Monthly Returns in % (σ_i)	Sharpe Ratio (SR_i)
Hedge Fund	0.857	1.206	0.429
Distressed Securities	1.075	0.786	0.935
Risk Arbitrage	0.456	0.771	0.151
Event Driven	0.976	1.027	0.619
Event Driven Multi-Strategy	0.935	1.319	0.451
Fixed Income Arbitrage	0.375	0.713	0.050
Convertible Arbitrage	0.458	1.260	0.094
Long/Short equity	0.965	1.827	0.342
Dedicated short bias	0.433	3.652	0.026
Equity Market Neutral	0.693	0.579	0.609
Global Macro	0.907	1.052	0.539
Managed Futures	0.357	2.830	0.006
Emerging Markets	1.481	2.329	0.490
Multi-strategy	0.878	1.088	0.494
S&P 500	0.712	2.066	0.180
MSCI World	1.048	2.206	0.321
Barclays US Aggregate	-0.143	0.916	-0.528
BofA Global Government Bond Index	0.009	1.727	-0.192

Table 4: Sharpe Ratio from January 2005 to January 2007

Specific Strategy/Index	Mean Monthly Return in % (r_i)	Standard Deviation of Monthly Returns in % (σ_i)	Sharpe Ratio (SR_i)
Hedge Fund	-0.271	2.473	-0.186
Distressed Securities	-0.566	2.135	-0.354
Risk Arbitrage	0.318	1.466	0.087
Event Driven	-0.268	2.225	-0.206
Event Driven Multi-Strategy	-0.081	2.421	-0.112
Fixed Income Arbitrage	-0.866	3.532	-0.299
Convertible Arbitrage	-0.740	4.001	-0.232
Long/Short equity	-0.235	2.973	-0.143
Dedicated short bias	0.477	5.213	0.055
Equity Market Neutral	-1.258	7.962	-0.182
Global Macro	0.504	2.540	0.124
Managed Futures	0.588	3.546	0.112
Emerging Markets	-0.391	4.114	-0.141
Multi-strategy	-0.454	2.625	-0.245
S&P 500	-1.548	7.584	-0.229
MSCI World	-1.629	7.693	-0.236
Barclays US Aggregate	0.054	1.246	-0.109
BofA Global Government Bond Index	0.638	2.413	0.185

Table 5: Sharpe Ratio from February 2007 to May 2009

Specific Strategy/Index	Mean Monthly Return in % (r_i)	Standard Deviation of Monthly Returns in % (σ_i)	Sharpe Ratio (SR_i)
Hedge Fund	0.647	1.699	0.375
Distressed Securities	0.699	1.861	0.371
Risk Arbitrage	0.319	1.031	0.300
Event Driven	0.558	2.317	0.237
Event Driven Multi-Strategy	0.478	2.672	0.176
Fixed Income Arbitrage	1.090	1.007	1.073
Convertible Arbitrage	1.151	1.859	0.614
Long/Short equity	0.358	2.494	0.140
Dedicated short bias	-1.041	4.761	-0.221
Equity Market Neutral	0.152	1.634	0.087
Global Macro	0.907	1.351	0.664
Managed Futures	0.415	3.383	0.120
Emerging Markets	0.685	2.667	0.253
Multi-strategy	0.778	1.394	0.552
S&P 500	0.668	4.927	0.134
MSCI World	0.415	5.324	0.076
Barclays US Aggregate	0.278	0.906	0.298
BofA Global Government Bond Index	0.622	2.127	0.288

Table 6: Sharpe Ratio from June 2009 to October 2011

Particularly, Table 4 depicts hedge funds performance along with the stock market and the bond market over the pre-crisis period (January 2005-January 2007). On a Sharpe Ratio basis, it is evident that all of the hedge fund indices were performing better than the bond market which presents negative results during this period. Compared to the stock market, nine out of fourteen hedge fund indices obtained higher performance than stocks. The results of event-driven risk arbitrage, fixed income arbitrage, convertible arbitrage, dedicated short bias and managed futures hedge funds were quite unfavorable compared to the stock market during this period. These results are rendered clearer to the following chart.

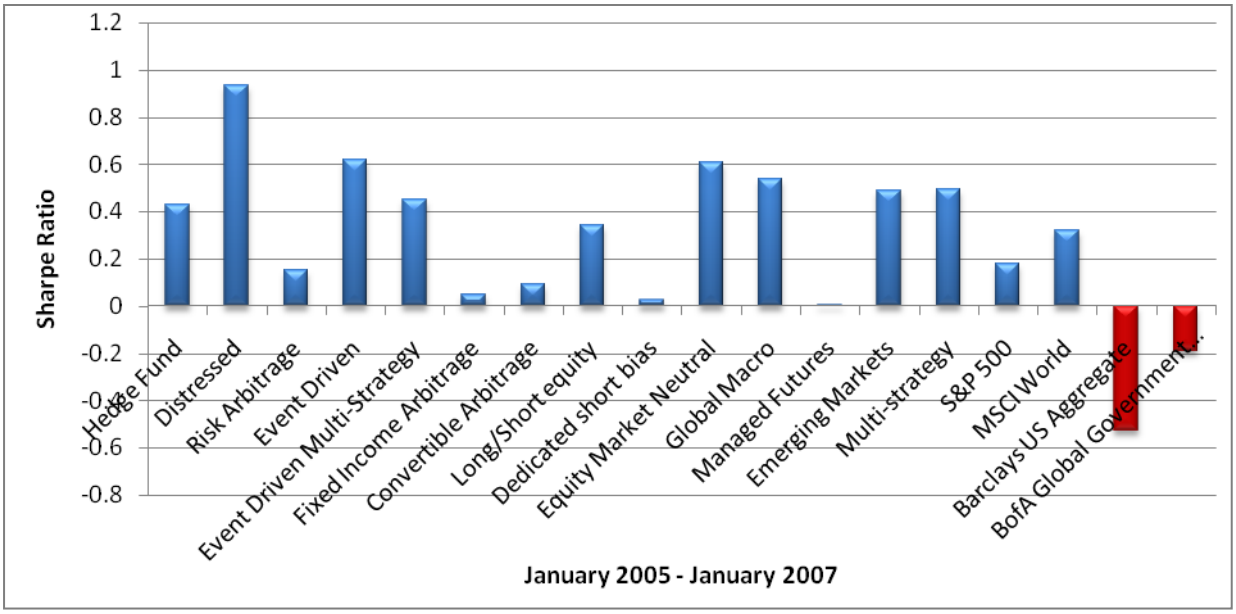

Chart 9: Sharpe Ratio from January 2005 to January 2007

Table 5 which presents the performance of hedge funds and traditional assets during the financial crisis (February 2007 – May 2009) nullifies the fact that hedge funds achieve superior performance compared to stocks and bonds especially during bear markets. It is remarkable that ten out of fourteen hedge fund indices have negative Sharpe Ratios which indicates that a riskless asset would perform better. At a certain extent this is true as the global government bond index (BofA Merill Lynch Global Government Bond Index) offers by far the best performance compared to hedge funds. Chart 10 depicts these results.

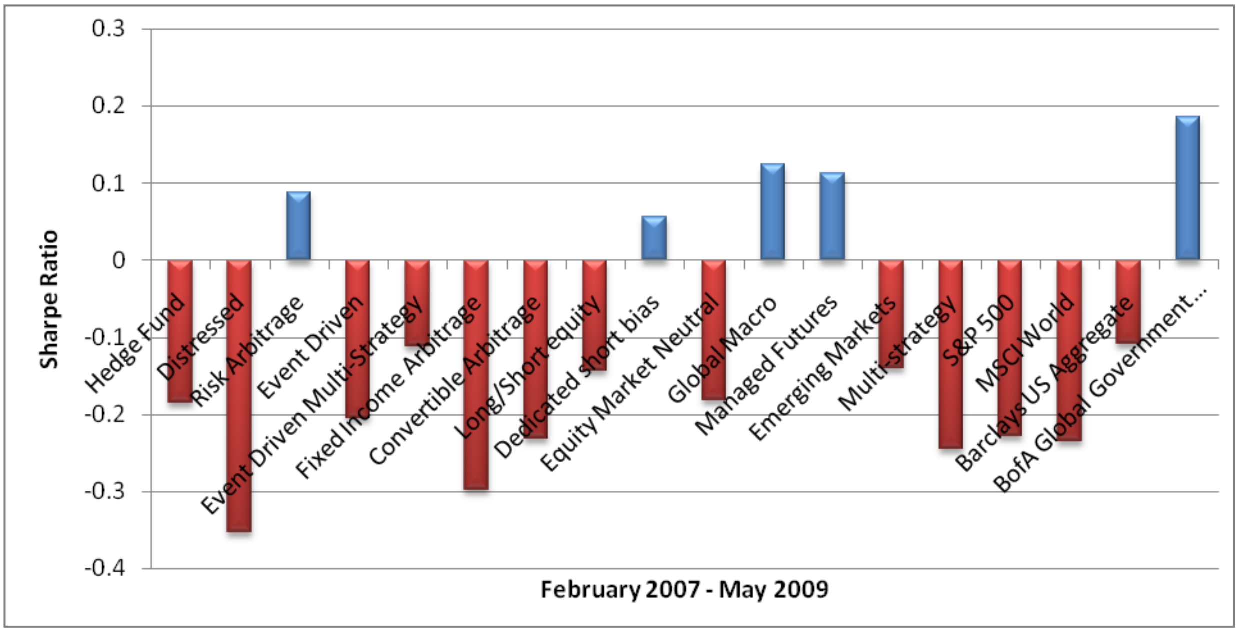

Chart 10: Sharpe Ratio from February 2007 to May 2009

Finally, during the post-credit crisis period (June 2009 – October 2011), hedge funds in fact outperform both the stock and bond market, apart from Dedicated Short Bias strategy that obtained a negative Sharpe Ratio, as shown in chart 11. In particular, Fixed Income Arbitrage, Convertible Arbitrage, Global Macro and Multi-Strategy hedge funds indices achieved exceptionally high returns given the level of volatility.

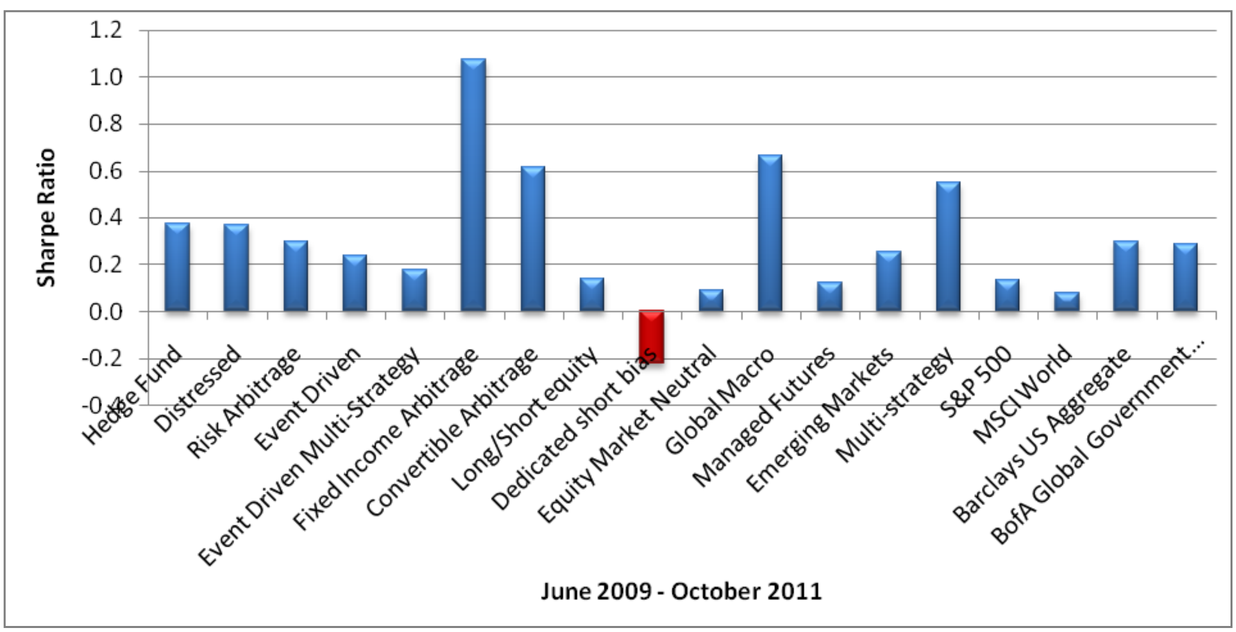

Chart 11: Sharpe Ratio from June 2009 to October 2011

4.2 Problems of classic performance measurement

4.2.1 The autocorrelation problem

These results, however, cannot be considered statistically significant based on recent literature which underlies that hedge fund returns present autocorrelation and deviate from normal distribution. The Sharpe Ratio is rooted in the CAPM. Assuming all asset returns to be normally distributed, the CAPM suggests that in equilibrium the highest attainable Sharpe ratio is that of the market index and therefore, a ratio higher than that indicates superior performance. Consequently, it is necessary to examine whether any of the above problems are evident to our sample.

First of all, as a matter of fact hedge fund returns are expected to be autocorrelated based on Lo (2002) who documents the fact that the presence of serial correlation in monthly returns generates an overestimation of as much as 65 percent of the annual Sharpe ratio; Jagannathan et al (2010) who discover that several hedge fund indices of their sample have significant first and second order autocorrelation and Liang (2003) who uses an autocorrelation-adjusted Sharpe Ratio and concludes that according to the period where the performance is measured, the autocorrelation of the hedge fund returns can have various impacts on the Sharpe ratio.

The serial correlation in hedge fund returns is caused, on the one hand, by the illiquid nature of the assets held by the hedge fund portfolios and, on the other hand, by the fund's manager compensation scheme. As far as the first reason is concerned, one of the hedge funds' specificities is to hold assets whose pricing is difficult to assess due to the existence of market frictions and illiquidity is one of the most common forms of such frictions. Since a market price is not available or available irregularly, subjectivity interferes for the valuation of the net asset values (NAV) of the fund, subjectivity either from the manager or from the specialized brokers who can be asked for this task. In such cases, this "subjective" pricing induces a serial correlation in their returns (Gallais-Hamonno and Nguyen-Thi-Thanh, 2007). Furthermore, the second reason is intertwined to the fact that a hedge fund manager has considerable discretion in marking the portfolio's value. Given the nature of hedge-fund compensation contracts and performance statistics, managers have an incentive to "smooth" their returns by marking their portfolios to less than their actual value in months with large positive returns so as to create a "cushion" for those months with lower returns. Such return smoothing behavior yields a more consistent set of returns over time with lower volatility and, therefore, a higher Sharpe ratio, but it also produces serial correlation as a side effect (Lo, 2001). Apart from that, the smoothing of the returns is helped by the lack of regulation and legal obligation to publish NAV.

Lo (2001) suggests the use of a significance test for the autocorrelation coefficients, the Ljung-Box test, to estimate the liquidity risk. When the latter is significant, it is necessary to correct the return series of the fund or the index before estimating its performance and risk. In order to examine whether or not the indices of our analysis are autocorrelated, the autocorrelation coefficients for up to two lags are estimated. In other words, the correlogram of each index is constructed[10]. We use a rule of thumb in order to deduce whether an autocorrelation coefficient is classed as significant or not. Specifically, a given autocorrelation coefficient is classed as significant if it is outside a $\pm 1.96 \times 1/(T)^{1/2}$ band, that is to say the 95% non-rejection region, where T is the number of observations (Brooks, 2008). Additionally, the Ljung-Box statistic is examined for two degrees of freedom at 10%, 5% and 1% level of significance. The Ljung-Box statistic is asymptotically distributed as a χ^2 under the null hypothesis that all of the autocorrelation coefficients are jointly zero. In our analysis, the indices of hedge fund strategies and traditional assets are autocorrelated when the Ljung-Box statistic of each index exceeds the relevant critical value, namely the value of 4.605, 5.991 and 9.210 at the 10%, 5% and 1% confidence level.

The integration of autocorrelation problem in hedge fund performance measurement is crucial. Two methods are especially suited for this task. Firstly, Asness, Crail and Liew (2001) use longer-horizon returns in order to identify the existence of autocorrelation on hedge fund indices. They suggest that in the absence of month-end pricing problems, which cause serial correlation on hedge funds returns as previously mentioned, annualized monthly standard deviation should be equal to annualized quarterly standard deviation. Based on this concept, we calculate the standard deviation not on basis of monthly returns but on the basis of quarterly returns and then, the monthly and quarterly values are annualized in order to compare them. The standard deviation of quarterly returns is expected to be higher than monthly standard deviation and thus, quarterly standard deviation is used for alleviating the effects of autocorrelation on

[10] The correlograms are obtained via EViews.

hedge fund performance. The annual standard deviation of a security i is calculated according to the type (Dorfleitner, 2002):

$$\sigma_i = \sqrt{[(1+r_i)^2 + \sigma_i^2)^\tau - (1+r_i)^{2\tau}}$$
,

where r_i stands for the monthly or quarterly returns and τ denotes the number of considered time intervals, namely $\tau = 12$ or 4 respectively.

The second method proposed in literature for dealing with the autocorrelation problem is known as the Geltner method. Geltner (1991, 1993) proposes a method that is widely used in the real estate sector which allows the first order autocorrelation to be eliminated. Amenc et al. (2005) suggest correcting the first order autocorrelation using the Geltner method (1991, 1993). They base their suggestion on the analysis of Okunev and White (2004)[11] which results for their data that only the first order autocorrelation coefficients are systematically significant in the case of alternative strategies and that the second order coefficients are only significant for some of the indices that represent convertible arbitrage and fixed-income arbitrage strategies. The Geltner method is calculated as follows:

$$R_t = \frac{R_t^* - \alpha R_{t-1}^*}{1-\alpha}$$
,

where R_t^* is the return observed at t, R_t the return that was really recorded at t, R_{t-1}^* the return observed at (t-1) and α the first order autocorrelation coefficient.

A key step in our analysis is to examine the impact of autocorrelation on standard deviation. Therefore, regardless of the Ljung-Box statistic results, the annual monthly and quarterly standard deviation is calculated for all the hedge fund strategies and traditional assets. Furthermore, it is important to define the order of autocorrelation. Although, it is easy to some extent to decide on the appropriate model orders from autocorrelation functions, the use of information criteria is applied in order to choose the correct model order. Based on this method it is required to choose the number of parameters, which minimizes the value of the information criteria. In particular, it is supposed that AR(1) and AR(2) models are plausible for the hedge fund strategies and traditional assets. The three most popular information criteria are Akaike's

[11] Okunev, J. and White D., 2004, An Analysis of the Risk Factors Underlying Hedge Fund Returns, in Intelligent Hedge Fund Investing, Ed. B. Schachter, Pub. RiskBooks.

information criterion (AIC), Schwarz's Bayesian information criterion (SBIC) and the Hannan-Quinn criterion (HQIC). Algebraically, these are expressed as follows:

$$\mathbf{AIC} = \ln(\sigma^2) + \frac{2k}{T}$$

$$\mathbf{SBIC} = \ln(\sigma^2) + \frac{k}{T}\ln T$$

$$\mathbf{HQIC} = \ln(\sigma^2) + \frac{2k}{T}\ln(\ln(T))$$

where σ^2 is the residual variance (also equivalent to the residual sum of squares divided by the number of observations, T), $k = p + q + 1$ is the total number of parameters estimated and T is the sample size (Brooks, 2008). It is worth noting that even though no criterion is definitely superior to others, SBIC embodies a much stiffer penalty term than AIC while HQIC is somewhere in between.

Finally, the autocorrelation problem is mitigated by applying the Geltner method on the indices that display first-order autocorrelation while, on the indices subjected to second order autocorrelation the adjusted standard deviation is used. The adjusted standard deviation is the recalculated version of the annual standard deviation of quarterly returns on a monthly basis.

4.2.2 The bias problem

In literature it is noted that hedge fund databases are mainly subject to two biases. The first is survivorship bias and the second common bias is backfill. As far as Dow Jones Credit Suisse Hedge Fund Database is concerned, new funds are added on a going forward basis only. Therefore, hedge fund history of good performance is not incorporated into the database and the database is not subject to backfill bias. On the other hand, hedge fund indices are affected by survivorship bias and for this reason, some adjustments are considered in order to integrate the bias problem into hedge fund performance measurement. Specifically, the returns of each hedge fund index must be minimized at some level due to the fact that the exclusion of funds that became defunct, the so-called "dead" funds, leads an index to be biased to the upside and the average hedge fund returns are overestimated.

Kaiser and Haberfelner (2011) find empirical evidence that the impact of survivorship bias has increased since the financial crisis. For the time period from January 2002 to December 2006, they estimated a survivorship bias of 0.33 percentage points per month while from January 2007 to September 2010, survivorship bias was estimated at 0.73 percentage points per month. Additionally, Ibbotson, Chen and Zhu (2010) studied hedge fund return data for January 1995-December 2009 from Dow Jones Credit Suisse Hedge Fund Database and estimated a survivorship bias of 0.43 percentage points per year. Consequently, during the financial crisis period (February 2007-May 2009) and during the post-credit crisis period (June 2009-October 2011), the bias problem is dealt with by reducing the hedge fund returns by 0.5 percentage points per month, which is approximately the average of these results.

Moreover, as far as the pre-crisis period is concerned, a bias adjustment of 0.2 percentage points per month is considered which is the average result of six studies using hedge fund returns from Dow Jones Credit Suisse Hedge Fund Database. In particular, Ammann and Moerth (2005) study the period from January 1994 to June 2003 and estimate a survivorship bias of 0.2 percentage points per month; Amin and Kat (2003) find a survivorship bias of 0.16% monthly for the period 1994-2001; Baquero, ter Horst and Verbeek (2005) estimate survivorship bias at 0.17% monthly for the time period 1994-2000; Barry (2003) estimate survivorship bias at 0.31% monthly; Fung and Hsieh (2006) estimate a survivorship bias of 0.2 percentage points per month for the period 1994-2004 and Liang (2001) document a monthly survivorship bias of 0.2% for the period 1990-1999.

4.2.3 The fat-tails problem

Assuming normally distributed returns appears to be inadequate in the case of hedge funds. Hedge funds use dynamic trading strategies, strategies involving buying or selling options and strategies that actively manage leverage. All these strategies create asymmetries and “fat tails” in return distributions. There are two statistical measures, known as skewness and kurtosis, used for quantifying these effects. Skewness is the third central moment of a distribution and measures the symmetry of a return around its mean. Kurtosis is the fourth central moment of a distribution and measures how fat the tails of a distribution are. A normal distribution is not skewed and is defined to have a coefficient of kurtosis of 3.

The Jarque-Bera test (1980) is used widespreadly in practice for testing normality of economic time series returns. The justification for this fact is the ease of computation of the JB statistic and the good performance of the test compared with others available in literature. The algorithm provides a joint test of the null hypothesis of normality in that the sample skewness b_1 equals zero and the sample kurtosis b_2 equals three. The null hypothesis is rejected when the JB statistic, $JB = n\left(\frac{\left(b_1^{1/2}\right)^2}{6} + \frac{(b_2-3)^2}{24}\right)$, exceeds the critical value which is taken in the asymptotic limit from the chi-square distribution with two degrees of freedom. The critical values at the 10%, 5% and 1% confidence level are $\chi^2_{(2,0.1)}$= 4.605, $\chi^2_{(2,0.5)}$=5.991 and $\chi^2_{(2,0.01)}$=9.210.

Despite its advantages, the use of the JB test leads to incorrect conclusions in the case of small- and medium-sized samples. Therefore, Urzua (1996) modified the JB statistic (AJB statistic) replacing the asymptotic mean and variances by their exact finite-sample values yielding

$$\mathbf{AJB} = \mathbf{n}\left(\frac{\left(\mathbf{b}_1^{1/2}\right)^2}{\mathbf{var}(\mathbf{b}_1^{1/2})} + \frac{(\mathbf{b}_2 - \mathbf{E}(\mathbf{b}_2))^2}{\mathbf{var}(\mathbf{b}_2)}\right),$$

where $b_1^{1/2}$ and b_2 are the coefficients of skewness and kurtosis respectively. The exact mean and variance of the standardized third and fourth moments are:

$$\mathbf{var}(\mathbf{b}_1^{1/2}) = \frac{\mathbf{6(n-2)}}{\mathbf{(n+1)(n+3)}},$$

where n is the number of observations

$$\mathbf{E}(\mathbf{b}_2) = \frac{\mathbf{3(n-1)}}{\mathbf{(n+1)}},$$

$$\mathbf{var}(\mathbf{b}_2) = \frac{\mathbf{24n(n-2)(n-3)}}{\mathbf{(n+1)^2(n+3)(n+5)}}$$

It is also noted that the AJB statistic has the same asymptotic distribution as the JB statistic.

In our analysis, we test for departures from normality in returns distributions based on the modified Jarque-Bera Statistic (AJB statistic).

As it is already mentioned, hedge fund returns are expected to exhibit a non-normal profile. Therefore, a risk measure that accounts for the higher moments of distributions must be applied. Such a measure is the modified Value-at-Risk (MVaR) presented by Favre and Galeano (2002). If MVaR is used to measure risk-adjusted performance the Modified Sharpe Ratio (MSR), described by the following equation, emerges:

$$\mathbf{MSR_i = \frac{r_i - r_f}{MVaR_i}}$$

The Modified Sharpe Ratio (MSR) has been employed by Gregoriou and Gueyie (2003) who underlie that the difference between the traditional and modified Sharpe Ratio is that, in the latter, the standard deviation is replaced by the modified VaR at a 5% confidence level. In our analysis, the Modified Sharpe Ratio (MSR) is calculated in order to integrate the fat-tail problem in performance measurement.

In particular, the final step in our analysis is to calculate the Adjusted Modified Sharpe Ratio ($AMSR_i$) that incorporates the adjustments for all the three problems under consideration as follows:

$$\mathbf{AMSR_i = \frac{(r_{Ai} - r_f)}{AMVaR_i}},$$

where r_{Ai} is the bias adjusted monthly hedge fund returns and $AMVaR_i$ is the adjusted modified Value-at-Risk that accounts for the autocorrelation problem and the fat-tail problem. The adjusted modified Value-at-Risk is calculated according to the following type:

$$\mathbf{MVaR_i = -(z_{CFi}\sigma_{Ai} + r_{Ai})w},$$

where σ_{Ai} is the monthly standard deviation adjusted for autocorrelation and $\mathbf{z_{CFi}}$ is the Cornish-Fisher expansion that adjusts for skewness and kurtosis.

CHAPTER 5

Alternative Hedge Fund performance measurement

In this section, the behaviour of hedge fund and traditional indices is examined during the time periods that were previously bracketed between bounds. The main objective is to identify whether or not the indices under examination are subject to autocorrelation, bias and fat-tails problem. Based on the aforementioned literature, it is expected to come up against these problems; therefore, the methodology previously discussed is applied in order to confront all three problems in one common framework.

5.1 The Pre-Crisis Period

Formation of an autocorrelation function plot, widely known as a correlogram, is certainly a primary step in identifying whether or not time series are autocorrelated. However, several, more accurate methods have been proposed for this purpose. As a first step in our analysis, we form the correlogram of each index for the time period from January 2005 to January 2007 in order to derive the values of autocorrelation coefficients[12].

During the pre-crisis period, where the number of observations T is 24, a correlation coefficient is classified as significant if it is bigger than approximately 0.400 or smaller than -0.400 at 5% significance level, based on the 95% non-rejection region rule. Under this rule, the first autocorrelation coefficient is only significant for the returns of Convertible Arbitrage Hedge Fund Index. Based on Ljung-Box statistic, the returns of S&P 500 present a relatively low probability of being autocorrelated, LB_i is significant at 5%, while the returns of Convertible Arbitrage Hedge Fund Index display significant serial autocorrelation at 1% significance level. The following table summarizes these results.

[12] The correlograms are obtained via EViews. See Appendix A.

	Autocorrelation	Coefficients	Ljung-Box Statistic
Index	α_{1i}	α_{2i}	LB_i
Hedge Fund	0.064	-0.010	0.1146
Distressed Securities	0.021	0.092	0.2537
Risk Arbitrage	-0.027	-0.040	0.0666
Event Driven	0.026	-0.025	0.036
Event Driven Multi-Strategy	0.017	-0.028	0.0305
Fixed Income Arbitrage	0.338	-0.154	3.7680
Convertible Arbitrage	0.615	0.204	11.431***
Long/Short equity	0.112	-0.028	0.3626
Dedicated short bias	0.358	0.104	3.7924
Equity Market Neutral	0.338	0.011	3.1018
Global Macro	-0.021	-0.024	0.0287
Managed Futures	-0.146	0.065	0.700
Emerging Markets	-0.103	-0.056	0.3739
Multi-strategy	0.309	-0.011	2.5993
S&P 500	-0.319	0.316	5.5963*
MSCI World	-0.153	0.210	1.8897
Barclays US Aggregate	0.067	-0.163	0.8753
BofA Global Government Bond Index	-0.189	-0.161	1.7091

Table 7: Correlogram data for the pre-crisis period

Furthermore, using the modified Jarque-Bera Statistic, we examine whether or not the distribution of hedge fund, equity and bond returns is symmetric and mesokurtic. Table 8 demonstrates that hedge fund returns and traditional assets returns fail to display a normal distribution. However, we cannot reject the null hypothesis of normality for BofA Global Government Bond Index.

Index	Skewness	Kurtosis	Modified Jarque-Bera statistic
Hedge Fund	-0.280243	2.348388	17.116167***
Distressed Securities	0.138741	2.214337	15.503662***
Risk Arbitrage	1.264056	6.713975	886.10986***
Event Driven	-0.611660	3.755730	89.675143***
Event Driven Multi-Strategy	-0.996791	5.121750	368.12294***
Fixed Income Arbitrage	-0.007765	3.356468	15.709685***
Convertible Arbitrage	-1.086484	4.302612	249.90034***
Long/Short equity	-0.491846	2.278797	39.909126***
Dedicated short bias	0.013261	1.976903	27.087308***
Equity Market Neutral	0.375610	2.662425	17.734925***
Global Macro	0.379498	3.074846	22.050095***
Managed Futures	-0.169358	1.898970	36.240971***
Emerging Markets	-0.963016	4.174064	202.06968***
Multi-strategy	-0.251883	2.142879	24.594947***
S&P 500	0.242959	2.268953	17.886758***
MSCI World	-0.322453	2.081874	33.056632***
Barclays US Aggregate	-0.026882	1.758841	44.326605***
BofA Global Government Bond Index	-0.046429	2.754823	0.2657402

Table 8: Modified Jarque-Bera Statistic for the pre-crisis period data

5.1.1 Autocorrelation adjustments

Even though the Ljung-Box statistic and the autocorrelation function plots refute the argument of our data being correlated, the autocorrelation problem is examined again since hedge funds invest in illiquid assets and marking-to-market problems tend to create lags in the evolution of hedge funds' net asset values showing up as autocorrelation in returns. This autocorrelation causes estimates of the standard deviation of hedge fund returns to exhibit a systematic downward bias (Kat, 2003). Following the analysis of Asness, Krail and Liew (2001), we estimate the standard deviation on the basis of quarterly returns[13]. Afterwards, the monthly and quarterly values are annualized in order to compare them. If the annual monthly standard deviation equals the annual quarterly standard deviation, the autocorrelation problem is not present to the specified index. This analysis is also applied to traditional indices.

[13] The data used are downloaded from Datastream Database on a quarterly basis.

The following table reveals that in all hedge fund and traditional indices the standard deviation does not remain unchanged. There is a sharp increase in Global Macro, Fixed Income Arbitrage and Convertible Arbitrage annualized quarterly standard deviation while a milder but significant increase is observed in Multi-Strategy, Dedicated Short Bias and Distressed Securities indices. On the other hand, the annualized quarterly standard deviation decreases for Managed Futures, Risk Arbitrage and Emerging Markets strategies by -13.31%, -9.96% and -4.04% respectively. Additionally, the annualized quarterly standard deviation declines for all traditional assets, except for Barclays US Aggregate Bond Index which rises by 5.68%.

Index	Annual monthly standard deviation (%)	Annual quarterly standard deviation (%)	% Change
Hedge Fund	4.59	4.87	6.05%
Distressed Securities	3.06	3.44	12.31%
Risk Arbitrage	2.81	2.53	-9.96%
Event Driven	3.96	4.05	2.25%
Event Driven Multi-Strategy	5.06	5.08	0.24%
Fixed Income Arbitrage	2.57	3.77	46.45%
Convertible Arbitrage	4.59	6.69	45.65%
Long/Short equity	7.04	7.21	2.41%
Dedicated Short Bias	13.32	16.27	22.14%
Equity Market Neutral	2.17	2.48	14.71%
Global Macro	2.17	4.01	85.29%
Managed Futures	10.22	8.86	-13.31%
Emerging Markets	9.50	9.11	-4.04%
Multi-strategy	4.15	5.32	28.29%
S&P 500	7.75	6.23	-19.63%
MSCI World	8.58	7.97	-7.06%
Barclays US Aggregate	3.12	3.30	5.68%
BofA Global Government Bond Index	5.99	3.91	-34.73%

Table 9: Annual monthly and quarterly standard deviation for the pre-crisis period data

The autocorrelation problem is mitigated by using the Geltner method for the time series subjected to first-order autocorrelation. In other words, we calculate the standard deviation of the returns produced by the type:

$$\mathbf{R}_t = \frac{\mathbf{R}_t^* - \alpha \mathbf{R}_{t-1}^*}{1-\alpha}.$$

Moreover, for the hedge fund indices that display second-order autocorrelation we use the annualized quarterly standard deviation which is divided by the root of 12 because we need the annual standard deviation of quarterly returns on a monthly basis.

Table 10 presents the order of autocorrelation displayed by the hedge fund strategies and traditional assets based on AIC and SBIC[14].

Index	AIC		SBIC		Result
	AR(1)	AR(2)	AR(1)	AR(2)	
Hedge Fund	*3.336*	3.467	*3.435*	3.616	AR(1)
Distressed Securities	*2.508*	2.625	*2.607*	2.774	AR(1)
Risk Arbitrage	*2.468*	2.609	*2.567*	2.757	AR(1)
Event Driven	*3.037*	3.164	*3.136*	3.312	AR(1)
Event Driven Multi-Strategy	*3.538*	3.666	*3.637*	3.815	AR(1)
Fixed Income Arbitrage	2.204	*2.201*	*2.303*	2.349	AR(1)
Convertible Arbitrage	*2.899*	2.947	*2.998*	3.095	AR(1)
Long/Short equity	*4.158*	4.278	*4.257*	4.427	AR(1)
Dedicated short bias	*5.283*	5.421	*5.382*	5.570	AR(1)
Equity Market Neutral	*1.780*	1.879	*1.879*	2.028	AR(1)
Global Macro	*3.110*	3.243	*3.209*	3.392	AR(1)
Managed Futures	*4.858*	4.982	*4.956*	5.131	AR(1)
Emerging Markets	*4.690*	4.800	*4.789*	4.948	AR(1)
Multi-strategy	*3.042*	3.166	*3.141*	3.315	AR(1)
S&P 500	*4.317*	4.394	*4.416*	4.543	AR(1)
MSCI World	*4.521*	4.604	*4.620*	4.753	AR(1)
Barclays US Aggregate	*2.824*	2.876	*2.922*	3.025	AR(1)
BofA Global Government Bond Index	*4.048*	4.143	*4.146*	4.291	AR(1)

Table 10: Order of autocorrelation for the pre-crisis period data

The result of the previous analysis is that hedge fund and traditional indices are subject to first order autocorrelation. In the case of Fixed Income Arbitrage hedge fund index this is not a clear result due to the fact that AIC suggests second order autocorrelation and SBIC first order autocorrelation as the correct order model for the index. We choose that this index exhibits first order autocorrelation based on SBIC which is considered a better measure in delivering the correct order model (Brooks, 2008).

[14] The equations are estimated on EViews.

The adjusted standard deviation of monthly returns for each index is presented to the following table:

Index	Adjusted Standard Deviation of monthly returns (%)
Hedge Fund	1.29
Distressed Securities	0.81
Risk Arbitrage	0.76
Event Driven	1.06
Event Driven Multi-Strategy	1.35
Fixed Income Arbitrage	1.03
Convertible Arbitrage	2.51
Long/Short equity	2.01
Dedicated short bias	4.96
Equity Market Neutral	0.89
Global Macro	1.05
Managed Futures	2.25
Emerging Markets	2.15
Multi-strategy	1.50
S&P 500	1.49
MSCI World	1.89
Barclays US Aggregate	0.99
BofA Global Government Bond Index	1.44

Table 11: Adjusted monthly standard deviation for the pre-crisis period data

5.1.2 Bias adjustments

Table 12 presents the reduced hedge fund monthly returns using the bias adjustment of 0.2 percentage points per month.

Index	Mean Monthly Return in % (r_i)	Adjusted Mean Monthly Return in % (r_{Ai})
Hedge Fund	0.857	0.657
Distressed Securities	1.075	0.875
Risk Arbitrage	0.456	0.256
Event Driven	0.976	0.776
Event Driven Multi-Strategy	0.935	0.735
Fixed Income Arbitrage	0.375	0.175
Convertible Arbitrage	0.458	0.258
Long/Short equity	0.965	0.765
Dedicated short bias	0.433	0.233
Equity Market Neutral	0.693	0.493
Global Macro	0.907	0.707
Managed Futures	0.357	0.157
Emerging Markets	1.481	1.281
Multi-strategy	0.878	0.678
S&P 500	0.712	0.712
MSCI World	1.048	1.048
Barclays US Aggregate	-0.143	-0.143
BofA Global Government Bond Index	0.009	0.009

Table 12: Bias adjusted mean monthly returns for the pre-crisis period data

5.1.3 Higher moment adjustments

Based on the results of the modified Jarque-Bera statistic, it is mandatory to calculate the modified Sharpe Ratio in order to account for tail-risk. Specifically, at this stage of analysis the Adjusted Modified Sharpe Ratio is calculated which incorporates the adjustments for all three problems under examination. Table 13 and chart 12 present the results.

Index	Adjusted Mean Monthly Return in % (r_{Ai})	Adjusted Standard Deviation of monthly returns in % (σ_{Ai})	Adjusted Modified Sharpe Ratio ($AMSR_i$)
Hedge Fund	0.657	1.29	0.210689
Distressed Securities	0.875	0.81	1.375685
Risk Arbitrage	0.256	0.76	-0.141123
Event Driven	0.776	1.06	0.409753
Event Driven Multi-Strategy	0.735	1.35	0.231898
Fixed Income Arbitrage	0.175	1.03	-0.113660
Convertible Arbitrage	0.258	2.51	-0.018755
Long/Short equity	0.765	2.01	0.156215
Dedicated short bias	0.233	4.96	-0.013880
Equity Market Neutral	0.493	0.89	0.185294
Global Macro	0.707	1.05	0.437513
Managed Futures	0.157	2.25	-0.051335
Emerging Markets	1.281	2.15	0.358400
Multi-strategy	0.678	1.50	0.184697
S&P 500	0.712	1.49	0.237540
MSCI World	1.048	1.89	0.329163
Barclays US Aggregate	-0.143	0.99	-0.276979
BofA Global Government Bond Index	0.009	1.44	-0.144008

Table 13: Adjusted modified Sharpe Ratio for the pre-crisis period data

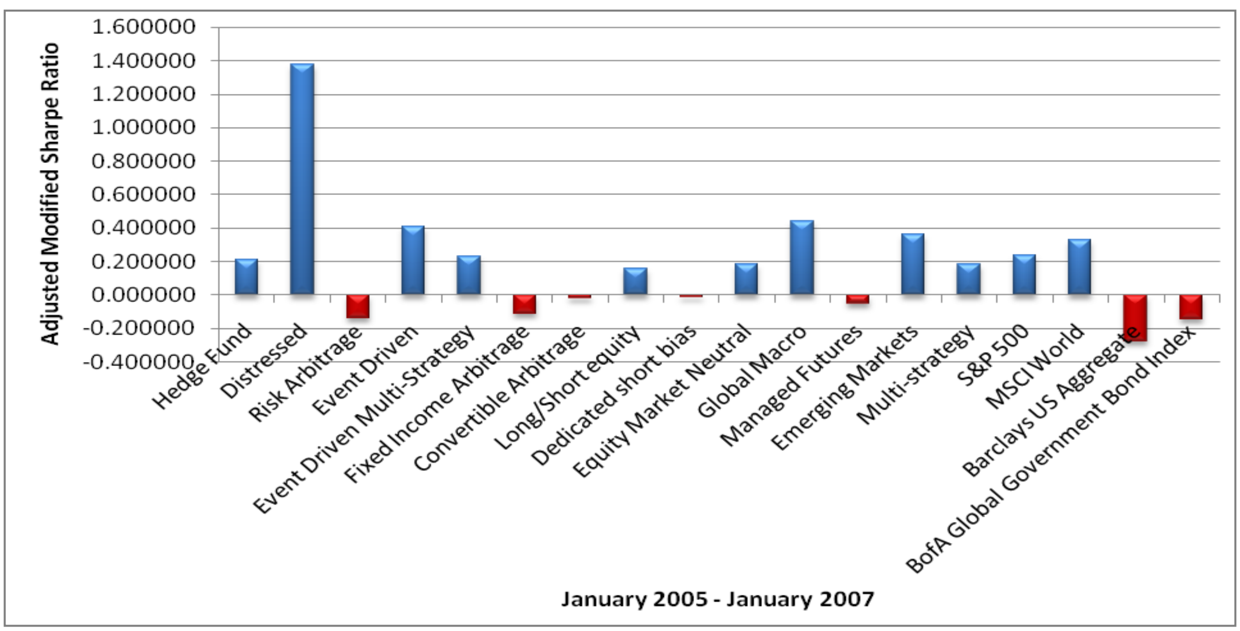

Chart12: Adjusted modified Sharpe Ratio for the pre-crisis period data

All things considered, it is remarkable that when autocorrelation, bias and fat tails problems are taken into account hedge funds are not considered as prosperous investment vehicles. Market indices are proved to perform better than several hedge fund indices such as Long/Short Equity, Equity Market Neutral and Multi-Strategy. To make matters worse, funds using Risk arbitrage, Fixed Income Arbitrage and Managed Futures strategies present negative returns. On the contrary, the Sharpe Ratio, as performance measure, indicated that the majority of hedge fund indices outperform market indices and all of the hedge fund indices exhibit positive performance.

5.2 The Crisis Period

First of all, the autocorrelation problem is examined for the bear market of February 2007 - May 2009. The analysis is based on autocorrelation function plots which are presented in Appendix A.

During the crisis period, where T=27, a correlation coefficient is classified as significant if it is bigger than approximately 0.377 or smaller than -0.377 at 5% significance level, based on the 95% non-rejection region rule. Under this rule, the first autocorrelation coefficient is significant for the returns of Hedge Fund Index, Distressed Securities, Risk Arbitrage, Event Driven, Fixed Income Arbitrage, Convertible Arbitrage, Global Macro, Emerging Markets and Multi-Strategy. Moreover, the second autocorrelation coefficient is significant for Managed Futures Hedge Fund Index and Barclays US Aggregate Bond Index. Based on Ljung-Box statistic, eleven out of fourteen hedge fund indices are autocorrelated while equity and bond indices do not display significant serial autocorrelation. The returns of Hedge Fund Index, Distressed Securities, Managed Futures and Multi-Strategy present a high probability of being correlated (LB_i significant at 1%). In addition to this, the returns of Risk Arbitrage, Event Driven, Fixed Income Arbitrage and Emerging Markets are autocorrelated at 5% significance level. Finally, the returns of Convertible Arbitrage, Long/short Equity and Global Macro are also autocorrelated but to smaller extent, at 10% significance level. Table 14 summarizes these results.

	Autocorrelation	Coefficients	Ljung-Box Statistic
Index	**α_{1i}**	**α_{2i}**	**LB_i**
Hedge Fund	0.511	0.254	9.8828***
Distressed Securities	0.567	0.352	13.573***
Risk Arbitrage	0.485	-0.007	7.0901**
Event Driven	0.377	0.302	7.122**
Event Driven Multi-Strategy	0.244	0.268	4.0392
Fixed Income Arbitrage	0.499	0.054	7.5807**
Convertible Arbitrage	0.435	0.071	5.8515*
Long/Short equity	0.401	0.156	5.5945*
Dedicated short bias	-0.012	-0.378	4.4728
Equity Market Neutral	0.007	-0.027	0.0239
Global Macro	0.413	-0.027	5.1635*
Managed Futures	0.221	-0.516	9.8128***
Emerging Markets	0.444	0.206	7.2770**
Multi-strategy	0.551	0.251	11.113***
S&P 500	0.094	-0.360	4.3335
MSCI World	0.189	-0.306	4.0146
Barclays US Aggregate	0.046	-0.378	4.5329
BofA Global Government Bond Index	0.056	-0.319	3.2871

Table 14: Correlogram data for the crisis period

Consequently, with reference to existing literature, the problem of autocorrelation in hedge fund returns is evident in our analysis for the time period from February 2007 to May 2009.

Furthermore, using the modified Jarque-Bera Statistic, we examine whether or not hedge fund, equity and bond returns are consistent with the normal distribution assumption. Based on the following table, hedge fund returns and traditional assets returns fail to follow the normal distribution. However, equity and bond indices values for skewness and excess kurtosis are less extreme than those shown for the hedge funds.

Index	Skewness	Kurtosis	Modified Jarque-Bera statistic
Hedge Fund	-1.085683	3.745588	226.37687***
Distressed Securities	-1.036326	3.308778	176.68444***
Risk Arbitrage	-0.686281	3.910379	137.323***
Event Driven	-0.773768	3.120112	96.370552***
Event Driven Multi-Strategy	-0.577521	3.162501	57.850018***
Fixed Income Arbitrage	-2.342681	8.498369	2535.5015***
Convertible Arbitrage	-1.732114	6.354873	1119.4526***
Long/Short equity	-0.921824	3.436377	150.61135***
Dedicated short bias	0.165445	2.366282	13.333586***
Equity Market Neutral	-4.666671	23.46718	25648.463***
Global Macro	-1.000629	4.208734	257.22949***
Managed Futures	0.031610	1.668798	65.353848***
Emerging Markets	-1.361179	5.513922	669.17154***
Multi-strategy	-1.120422	4.109029	281.33563***
S&P 500	-0.100627	3.121566	7.4265104**
MSCI World	-0.178286	2.961226	6.4160691**
Barclays US Aggregate	0.534945	3.646448	81.990737***
BofA Global Government Bond Index	0.180235	2.932544	6.0384951**

Table 15: Modified Jarque-Bera Statistic for the crisis period data

5.2.1 Autocorrelation adjustments

The first step in integrating the autocorrelation problem in hedge fund performance measurement is to estimate the standard deviation on the basis of quarterly returns[15]. Afterwards, the monthly and quarterly values are annualized in order to compare them.

Table 16 reveals that in all hedge fund indices, except Managed Futures, annualized quarterly standard deviation is higher than annualized monthly standard deviation. For example, Risk Arbitrage, Emerging Markets and Long/Short Equity Hedge Fund indices experience the greatest increase in standard deviation by 53.51%, 40.22% and 33.67% respectively. In addition, Equity Market Neutral and Dedicated Short Bias strategies expose the slightest increase by 0.52% and 4.48% respectively. On the other hand, the standard deviation declines for all traditional assets, except for Barclays US Aggregate Bond Index which rises by 22.44%.

[15] The data used are downloaded from Datastream Database on a quarterly basis.

Index	Annual monthly standard deviation (%)	Annual quarterly standard deviation (%)	% Change
Hedge Fund	8.33	10.85	30.29%
Distressed Securities	6.96	9.07	30.38%
Risk Arbitrage	5.26	8.08	53.51%
Event Driven	7.49	9.51	26.93%
Event Driven Multi-Strategy	8.33	10.40	24.94%
Fixed Income Arbitrage	11.16	14.18	27.05%
Convertible Arbitrage	12.83	16.91	31.79%
Long/Short equity	10.06	13.45	33.67%
Dedicated Short Bias	19.17	20.03	4.48%
Equity Market Neutral	24.43	24.56	0.52%
Global Macro	9.32	12.12	30.07%
Managed Futures	13.15	7.53	-42.75%
Emerging Markets	13.72	19.23	40.22%
Multi-strategy	8.67	11.12	28.34%
S&P 500	22.49	16.94	-24.68%
MSCI World	22.62	20.84	-7.89%
Barclays US Aggregate	4.34	5.32	22.44%
BofA Global Government Bond Index	8.98	7.76	-13.54%

Table 16: Annual monthly and quarterly standard deviation for the crisis period data

The autocorrelation problem is mitigated by using the Geltner method for the time series subjected to first-order autocorrelation and for the hedge fund indices that display second-order autocorrelation we use the annualized quarterly standard deviation divided by the root of 12.

Table 17 presents the order of autocorrelation displayed by the hedge fund strategies and traditional assets based on AIC and SBIC[16].

[16] The equations are estimated on EViews.

Index	AIC		SBIC		Result
	AR(1)	AR(2)	AR(1)	AR(2)	
Hedge Fund	*4.482*	4.598	*4.579*	4.745	AR(1)
Distressed Securities	*4.055*	4.169	*4.151*	4.315	AR(1)
Risk Arbitrage	*3.471*	3.480	*3.567*	3.626	AR(1)
Event Driven	*4.403*	4.481	*4.499*	4.627	AR(1)
Event Driven Multi-Strategy	*4.671*	4.736	*4.768*	4.883	AR(1)
Fixed Income Arbitrage	*5.203*	5.257	*5.300*	5.403	AR(1)
Convertible Arbitrage	*5.527*	5.627	*5.624*	5.773	AR(1)
Long/Short equity	*4.984*	5.094	*5.081*	5.240	AR(1)
Dedicated short bias	6.293	*6.212*	6.390	*6.358*	AR(2)
Equity Market Neutral	*7.139*	7.258	*7.235*	7.404	AR(1)
Global Macro	*4.669*	4.731	*4.765*	4.878	AR(1)
Managed Futures	5.385	*4.968*	5.482	*5.114*	AR(2)
Emerging Markets	*5.575*	5.692	*5.671*	5.838	AR(1)
Multi-strategy	*4.518*	4.635	*4.615*	4.782	AR(1)
S&P 500	7.032	*6.948*	7.129	*7.095*	AR(2)
MSCI World	7.032	*6.982*	7.129	*7.128*	AR(2)
Barclays US Aggregate	3.401	*3.353*	3.498	*3.499*	AR(2)
BofA Global Government Bond Index	*4.736*	4.744	*4.833*	4.890	AR(1)

Table 17: Order of autocorrelation for the crisis period data

Based on previous analysis we deduce that twelve out of fourteen hedge fund strategies present first-order autocorrelation. Specifically, this statement is valid for the aggregated Hedge Fund Index, Distressed Securities, Risk Arbitrage, Event-Driven, Event-Driven Multi-strategy, Fixed Income Arbitrage, Convertible Arbitrage, Long/Short Equity, Equity Market Neutral, Global Macro, Emerging Markets and Multi-Strategy hedge fund indices. Furthermore, only Dedicated Short Bias and Managed Futures hedge fund strategies present second-order autocorrelation. In contrast, S&P 500, MSCI World Index and Barclays US Aggregate Bond index are subject to second-order autocorrelation whereas BofA Global Government Bond Index presents first-order autocorrelation. For these indices, the information criteria, AIC and SBIC, deliver the same result as far as the correct model order is concerned.

The adjusted standard deviation of monthly returns for each index is presented to the following table:

Index	Adjusted Standard Deviation of monthly returns (%)
Hedge Fund	4.39
Distressed Securities	4.01
Risk Arbitrage	2.52
Event Driven	3.32
Event Driven Multi-Strategy	3.13
Fixed Income Arbitrage	6.15
Convertible Arbitrage	6.42
Long/Short equity	4.61
Dedicated short bias	5.78
Equity Market Neutral	8.17
Global Macro	4.02
Managed Futures	2.17
Emerging Markets	6.68
Multi-strategy	4.88
S&P 500	4.89
MSCI World	6.02
Barclays US Aggregate	1.54
BofA Global Government Bond Index	2.58

Table 18: Adjusted monthly standard deviation for the crisis period data

5.2.2 Bias adjustments

The following table presents the reduced hedge fund monthly returns using the bias adjustment of 0.5 percentage points per month.

Index	Mean Monthly Return in % (r_i)	Adjusted Mean Monthly Return in % (r_{Ai})
Hedge Fund	-0.271	-0.771
Distressed Securities	-0.566	-1.066
Risk Arbitrage	0.318	-0.182
Event Driven	-0.268	-0.768
Event Driven Multi-Strategy	-0.081	-0.581
Fixed Income Arbitrage	-0.866	-1.366
Convertible Arbitrage	-0.740	-1.24
Long/Short equity	-0.235	-0.735
Dedicated short bias	0.477	-0.023
Equity Market Neutral	-1.258	-1.758
Global Macro	0.504	0.004
Managed Futures	0.588	0.088
Emerging Markets	-0.391	-0.891
Multi-strategy	-0.454	-0.954
S&P 500	-1.548	-1.548
MSCI World	-1.629	-1.629
Barclays US Aggregate	0.054	0.054
BofA Global Government Bond Index	0.638	0.638

Table 19: Bias adjusted mean monthly returns for the crisis period data

5.2.3 Higher moment adjustments

Based on previous analysis, it is necessary to calculate the Adjusted Modified Sharpe Ratio in order to take into account autocorrelation, bias and fat-tails problems. The following table and chart present the results.

Index	Adjusted Mean Monthly Return in % (r_{Ai})	Adjusted Standard Deviation of monthly returns in % (σ_{Ai})	Adjusted Modified Sharpe Ratio ($AMSR_i$)
Hedge Fund	-0.771	4.39	-0.107763
Distressed Securities	-1.066	4.01	-0.147861
Risk Arbitrage	-0.182	2.52	-0.080914
Event Driven	-0.768	3.32	-0.142713
Event Driven Multi-Strategy	-0.581	3.13	-0.127991
Fixed Income Arbitrage	-1.366	6.15	-0.112034
Convertible Arbitrage	-1.24	6.42	-0.095003
Long/Short equity	-0.735	4.61	-0.101287
Dedicated short bias	-0.023	5.78	-0.023721
Equity Market Neutral	-1.758	8.17	-0.103490
Global Macro	0.004	4.02	-0.025359
Managed Futures	0.088	2.17	-0.030100
Emerging Markets	-0.891	6.68	-0.080148
Multi-strategy	-0.954	4.88	-0.114224
S&P 500	-1.548	4.89	-0.184457
MSCI World	-1.629	6.02	-0.158549
Barclays US Aggregate	0.054	1.54	-0.064051
BofA Global Government Bond Index	0.638	2.58	0.134969

Table 20: Adjusted modified Sharpe Ratio for the crisis period data

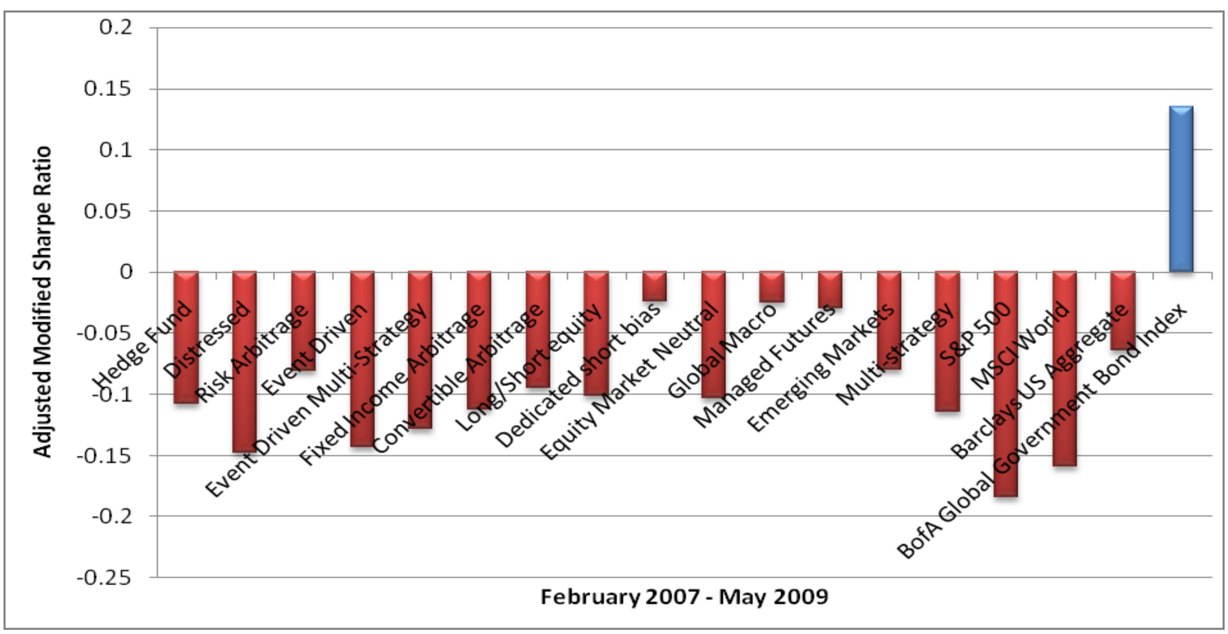

Chart13: Adjusted modified Sharpe Ratio for the crisis period data

Overall, it is obvious that the inefficiency of hedge funds is heightened when additionally considering the autocorrelation, bias and fat-tail problem. This is a valid statement even for the case of Risk Arbitrage, Dedicated Short Bias, Global Macro and Managed Futures strategies that seemed to perform better than market indices based on the Sharpe Ratio due to the fact that based on the $AMSR_i$, even these strategies demonstrate a negative performance.

5.3 The Post-Credit Crisis Period

The autocorrelation problem is examined herein for the time period of June 2009 to October 2011. The analysis is based on the autocorrelation function plots presented in Appendix A.

During the post-crisis period, where T=29, a correlation coefficient is classified as significant if it is bigger than approximately 0.364 or smaller than -0.364 at 5% significance level, based on the 95% non-rejection region rule. Under this rule, some preliminary results are presented in this section. The first autocorrelation coefficient is significant for the returns of Convertible Arbitrage, Distressed Securities, Event Driven Multi-Strategy, Event Driven, Fixed Income Arbitrage, Global Macro and Multi-Strategy. Based on the Ljung-Box statistic, seven out of fourteen hedge fund indices are autocorrelated while equity and bond indices do not display significant serial autocorrelation. The returns of Convertible Arbitrage Hedge Fund Index exhibit a high probability of being correlated (LB_i significant at 1%). In addition to this, the returns of Distressed Securities, Event Driven, Event Driven Multi-Strategy and Fixed Income Arbitrage are autocorrelated at 5% significance level while Global Macro and Multi-Strategy are also autocorrelated but to smaller extent, at 10% significance level. Table 21 depicts these results.

	Autocorrelation	Coefficients	Ljung-Box Statistic
Index	**α_{1i}**	**α_{2i}**	**LB_i**
Hedge Fund	0.191	0.081	1.3515
Distressed Securities	0.443	0.175	7.0825**
Risk Arbitrage	0.157	0.035	0.8050
Event Driven	0.441	0.203	7.3828**
Event Driven Multi-Strategy	0.426	0.208	7.0576**
Fixed Income Arbitrage	0.409	0.350	9.1738**
Convertible Arbitrage	0.523	0.216	10.029***
Long/Short equity	0.204	0.091	1.5654
Dedicated short bias	0.144	0.158	1.4534
Equity Market Neutral	-0.040	-0.126	0.5648
Global Macro	-0.413	0.089	5.5567*
Managed Futures	-0.321	0.003	3.2122
Emerging Markets	0.149	-0.128	1.2199
Multi-strategy	0.375	0.141	5.0151*
S&P 500	0.039	-0.050	0.1258
MSCI World	0.053	-0.063	0.2135
Barclays US Aggregate	0.028	0.164	0.8915
BofA Global Government Bond Index	-0.107	-0.029	0.3854

Table 21: Correlogram data for the post-credit crisis period

Even though the problem of autocorrelation in hedge fund returns is not as prominent as it was proved to be during the financial crisis period, it is imperative to be taken into account for hedge fund performance measurement.

Moreover, hedge fund, equity and bond returns are tested for deviating from normality by applying the modified Jarque-Bera Statistic. Based on the following table, all of the hedge fund returns, except Equity Market Neutral returns, and traditional assets returns fail to display a normal distribution. Additionally, equity and bond indices values for skewness and excess kurtosis are substantially significant.

Index	Skewness	Kurtosis	Modified Jarque-Bera statistic
Hedge Fund	-0.557151	2.796378	50.089198***
Distressed Securities	-1.071823	3.750003	235.86857***
Risk Arbitrage	-0.292462	2.385652	22.957534***
Event Driven	-1.088793	3.679528	234.62044***
Event Driven Multi-Strategy	-0.993595	3.590841	194.39535***
Fixed Income Arbitrage	0.338392	3.023220	21.397481***
Convertible Arbitrage	0.216764	3.073676	11.923191***
Long/Short equity	-0.473264	2.775842	36.157424***
Dedicated short bias	0.225581	2.478800	13.659143***
Equity Market Neutral	0.076917	2.865948	1.247281
Global Macro	0.051920	1.978881	36.997245***
Managed Futures	-0.012591	1.668544	69.770386***
Emerging Markets	-0.973956	4.679239	349.26077***
Multi-strategy	-0.706668	3.129675	86.829563***
S&P 500	-0.421321	2.852667	28.838718***
MSCI World	-0.196135	2.967706	7.88862**
Barclays US Aggregate	-0.728210	2.683830	86.22555***
BofA Global Government Bond Index	-1.033556	4.431870	320.47871***

Table 22: Modified Jarque-Bera Statistic for the post-credit crisis period data

5.3.1 Autocorrelation adjustments

The annualized standard deviation of monthly and quarterly returns[17], estimated herein, was also examined in comparison in order to confirm the presence of autocorrelation in hedge fund strategies and traditional indices.

The percentage change depicted to the following table indicates that the autocorrelation problem cannot be avoided.

[17] The data used are downloaded from Datastream Database on a monthly and quarterly basis.

Index	Annual monthly standard deviation (%)	Annual quarterly standard deviation (%)	% Change
Hedge Fund	6.32	6.11	-3.34%
Distressed Securities	6.97	8.25	18.39%
Risk Arbitrage	3.70	3.54	-4.43%
Event Driven	8.55	10.19	19.19%
Event Driven Multi-Strategy	9.78	11.66	19.23%
Fixed Income Arbitrage	3.93	5.48	39.43%
Convertible Arbitrage	7.31	10.69	46.33%
Long/Short equity	9.00	8.84	-1.80%
Dedicated Short Bias	14.79	15.48	4.67%
Equity Market Neutral	5.76	5.10	-11.46%
Global Macro	5.19	3.77	-27.41%
Managed Futures	12.30	9.11	-25.93%
Emerging Markets	9.98	7.01	-29.80%
Multi-strategy	5.26	6.06	15.18%
S&P 500	18.48	14.92	-19.28%
MSCI World	19.45	16.21	-16.68%
Barclays US Aggregate	3.24	3.30	2.01%
BofA Global Government Bond Index	7.90	8.71	10.31%

Table 23: Annual monthly and quarterly standard deviation for the post-credit crisis period data

Keeping the aforementioned methodology in mind, the autocorrelation problem is mitigated by using the Geltner method for the time series subjected to first-order autocorrelation while for hedge fund and traditional indices that display second-order autocorrelation we use the annualized quarterly standard deviation which is divided by the root of 12. The table below presents the order of autocorrelation displayed by the hedge fund strategies and traditional assets based on AIC and SBIC[18].

[18] The equations are estimated on EViews.

Index	AIC		SBIC		Result
	AR(1)	**AR(2)**	**AR(1)**	**AR(2)**	
Hedge Fund	*3.999*	4.053	*4.095*	4.198	AR(1)
Distressed Securities	*3.947*	4.029	*4.043*	4.174	AR(1)
Risk Arbitrage	*3.006*	3.105	*3.102*	3.250	AR(1)
Event Driven	*4.374*	4.438	*4.470*	4.583	AR(1)
Event Driven Multi-Strategy	*4.679*	4.737	*4.775*	4.883	AR(1)
Fixed Income Arbitrage	2.776	*2.473*	2.872	2.*618*	AR(2)
Convertible Arbitrage	3.714	*3.605*	3.810	*3.751*	AR(2)
Long/Short equity	*4.759*	4.815	*4.788*	4.960	AR(1)
Dedicated short bias	*6.080*	6.092	6.*176*	6.237	AR(1)
Equity Market Neutral	*3.964*	4.028	*4.060*	4.173	AR(1)
Global Macro	*3.232*	3.433	*3.419*	3.579	AR(1)
Managed Futures	*5.285*	5.377	*5.381*	5.522	AR(1)
Emerging Markets	*4.912*	4.947	*5.008*	5.093	AR(1)
Multi-strategy	*3.438*	3.454	*3.534*	3.599	AR(1)
S&P 500	*6.161*	6.170	*6.257*	6.316	AR(1)
MSCI World	6.318	*6.308*	*6.413*	6.454	AR(1)
Barclays US Aggregate	*2.771*	2.854	*2.867*	2.999	AR(1)
BofA Global Government Bond Index	*4.482*	4.585	*4.578*	4.730	AR(1)

Table 24: Order of autocorrelation for the post-credit crisis period data

In the case of MSCI World Index, there is no consensus, based on the information criteria, on the model order. Therefore, we choose that MSCI World Index is subject to first-order correlation as the SBIC suggests, due to the fact that SBIC is considered to be a better measure in delivering the correct order model (Brooks, 2008). However, the estimation of AIC and SBIC for the remainder of the indices result in the same model order. Particularly, Hedge Fund, Distressed Securities, Risk Arbitrage, Event Driven, Event Driven Multi-Strategy, Long/Short equity, Dedicated short bias, Equity Market Neutral, Global Macro, Managed Futures, Emerging Markets, Multi-strategy, S&P 500, MSCI World, Barclays US Aggregate and BofA Global Government Bond Index exhibit first-order autocorrelation and only two hedge fund strategies, Fixed Income Arbitrage and Convertible Arbitrage, display second-order autocorrelation.

Consequently, the adjusted standard deviation of monthly returns for each index is presented to the following table:

Index	Adjusted Standard Deviation of monthly returns (%)
Hedge Fund	2.09
Distressed Securities	2.97
Risk Arbitrage	1.22
Event Driven	3.68
Event Driven Multi-Strategy	4.18
Fixed Income Arbitrage	1.58
Convertible Arbitrage	3.09
Long/Short equity	3.11
Dedicated short bias	5.60
Equity Market Neutral	1.60
Global Macro	0.85
Managed Futures	2.44
Emerging Markets	3.15
Multi-strategy	2.05
S&P 500	5.19
MSCI World	5.69
Barclays US Aggregate	0.94
BofA Global Government Bond Index	1.95

Table 25: Adjusted monthly standard deviation for the post-credit crisis period data

5.3.2. Bias adjustments

To reflect the bias problem the mean monthly return of each index was truncated at 0.5 percentage points. The results are presented to the following table.

Index	Mean Monthly Return in % (r_i)	Adjusted Mean Monthly Return in % (r_{Ai})
Hedge Fund	0.647	0.147
Distressed Securities	0.699	0.199
Risk Arbitrage	0.319	-0.181
Event Driven	0.558	0.058
Event Driven Multi-Strategy	0.478	-0.022
Fixed Income Arbitrage	1.090	0.590
Convertible Arbitrage	1.151	0.651
Long/Short equity	0.358	-0.142
Dedicated short bias	-1.041	-1.541
Equity Market Neutral	0.152	-0.348
Global Macro	0.907	0.407
Managed Futures	0.415	-0.085
Emerging Markets	0.685	0.185
Multi-strategy	0.778	0.278
S&P 500	0.668	0.668
MSCI World	0.415	0.415
Barclays US Aggregate	0.278	0.278
BofA Global Government Bond Index	0.622	0.622

Table 26: Bias adjusted mean monthly returns for the post-credit crisis period data

5.3.3 Higher moment adjustments

In this section, the Adjusted Modified Sharpe Ratio is calculated in replacement of the Sharpe Ratio as a performance measure. The following table and chart present the results.

Index	Adjusted Mean Monthly Return in % (r_{Ai})	Adjusted Standard Deviation of monthly returns in % (σ_{Ai})	Adjusted Modified Sharpe Ratio ($AMSR_i$)
Hedge Fund	0.642	2.09	0.211238
Distressed Securities	0.694	2.97	0.142493
Risk Arbitrage	0.314	1.22	0.175950
Event Driven	0.553	3.68	0.086572
Event Driven Multi-Strategy	0.473	4.18	0.064421
Fixed Income Arbitrage	1.085	1.58	0.852552
Convertible Arbitrage	1.146	3.09	0.320119
Long/Short equity	0.353	3.11	0.068888
Dedicated short bias	-1.046	5.60	-0.109752
Equity Market Neutral	0.147	1.60	0.058547
Global Macro	0.902	0.85	1.986242
Managed Futures	0.410	2.44	0.113597
Emerging Markets	0.680	3.15	0.133671
Multi-strategy	0.773	2.05	0.266942
S&P 500	0.663	5.19	0.080743
MSCI World	0.410	5.69	0.045533
Barclays US Aggregate	0.273	0.94	0.191805
BofA Global Government Bond Index	0.617	1.95	0.208161

Table 27: Adjusted modified Sharpe Ratio for the post-credit crisis period data

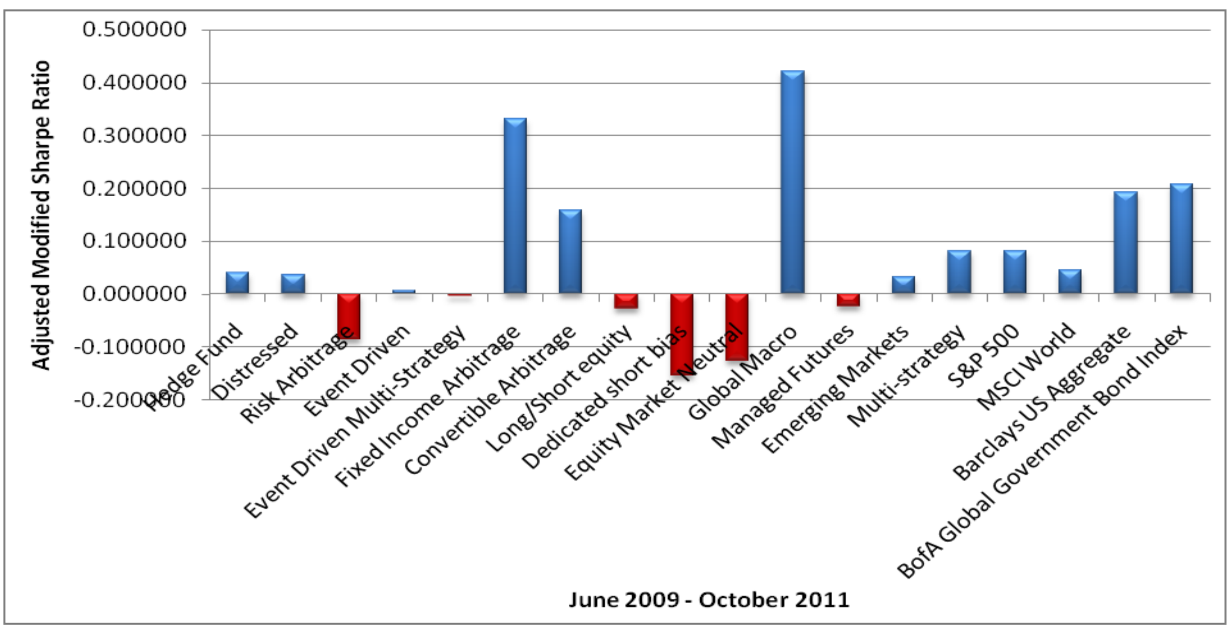

Chart 14: Adjusted modified Sharpe Ratio for the post-credit crisis period data

Based on the results of the Adjusted Modified Sharpe Ratio, it is easy to infer that hedge funds do not seem to be a wise investment decision. Funds using Risk Arbitrage, Event-Driven Multi-Strategy, Long/Short Equity, Dedicated Short Bias, Equity Market Neutral and Managed Futures strategies exhibit negative performance. Of course, this fact was not obvious on the Sharpe Ratio analysis. In this case where autocorrelation, bias and fat-tail problems are taken into account, investing in stocks and bonds seems to definitely be more promising than investing in hedge funds. However, funds using Fixed Income Arbitrage, Convertible Arbitrage and Global Macro strategies continue to outperform market indices.

CHAPTER 6

Portfolio Optimization

The previous chapters demonstrated whether or not hedge funds can be attractive investment vehicles as standalone assets during three different time intervals. The analysis focused on the examination and correction of autocorrelation, bias and fat-tails problems that can lead to erroneous results if not taken into account. This chapter is concerned with the combination of hedge funds with stocks and bonds in a portfolio.

In general, under the portfolio context, the core competency of hedge funds is explained by the concept of diversification. Hedge funds are considered to be uncorrelated or to exhibit low correlation with traditional assets, namely stocks and bonds, and the effect of this diversification is to significantly reduce portfolio risk and achieve higher returns. In our analysis in order to examine the effect of diversification, we firstly examine the correlations of the indices' returns estimating the Pearson correlation coefficient of hedge fund returns among themselves as well as compared to stock and bond returns.

Furthermore, the efficiency of hedge funds in an investment portfolio is examined in the mean-variance framework of Markowitz, which formalises the idea that out of all possible portfolios a risk-averse investor will only be interested in those portfolios that offer the highest expected return for a given level of standard deviation. However, the classical Markowitz approach focus only on the mean and standard deviation and skips over the fact that hedge fund attractive mean-variance attributes tend to go hand in hand with unattractive skewness and kurtosis properties. To make matters worse, hedge funds are rendered less appealing considering the fact that hedge fund returns are subject to specific biases.

In our analysis two mean-variance optimizations are performed; the first one with only stocks and bonds and the second one with stocks, bonds and hedge funds. Specifically, we use the returns of S&P 500, Barclays US Aggregate Bond Index and Hedge Fund Aggregate Index. Additionally, to transfer the concept of hedge fund returns adjustments to the portfolio framework, we perform a portfolio optimization based on the portfolio value at risk, whose results are almost identical with those derived from classical Markowitz optimization, and on the portfolio adjusted modified value at risk, whose results take into consideration autocorrelation, bias and fat-tails. This two-step approach allows us to compare the results of traditional and adjusted hedge fund portfolio optimization.

The calculations of this method are based on the portfolio weights which are derived from the classical portfolio optimization. Afterwards, the value at risk and the adjusted modified value at risk are calculated by:

$$\mathbf{VaR_p = -(z_\alpha \sigma_p + r_p)w,}$$

$$\mathbf{z_{CF_p} = z_C + \frac{1}{6}(z_C{}^2 - 1)S_p + \frac{1}{24}(z_C{}^3 - 3z)K_p - \frac{1}{36}(2z_C{}^3 - 5z_C)S_p^2,}$$

$$\mathbf{AMVaR_p = -(z_{CFp}\sigma_p + r_p)w}$$

Under the constraints that:

$$\sum_{i=1}^{n} x_i = 1$$

and $\mathbf{x_i \geq 0.}$

In general, for a two asset portfolio we calculate portfolio return and portfolio variance according to the following types:

$$r_p = \sum_{i=1}^{n} x_i r_i,$$

$$\sigma_p^2 = w_A^2\sigma_A^2 + w_B^2\sigma_B^2 + 2w_A w_B \sigma_A \sigma_B \rho_{AB}$$

For a three asset portfolio we similarly have:

$$r_p = \sum_{i=1}^{n} x_i r_i,$$

$$\sigma_p^2 = w_A^2\sigma_A^2 + w_B^2\sigma_B^2 + w_C^2\sigma_C^2 + 2w_A w_B \sigma_A \sigma_B \rho_{AB} + 2w_A w_C \sigma_A \sigma_C \rho_{AC} + 2w_B w_C \sigma_B \sigma_C \rho_{BC}$$

This procedure is applied to all three time intervals under examination.

6.1 The Pre-Crisis Period

The first step of the portfolio analysis is based on the correlations of the indices' returns. For this case, the Pearson correlation coefficients of all the asset pairs are shown in the following figure[19]. As it can be easily inferred from this figure, the correlation of hedge fund returns with bonds is negative or positive but in both cases remains at low levels. On the other hand, hedge funds show large positive or negative correlated returns to stocks. Consequently, a portfolio constructed from bonds and hedge funds is considered to be a prosperous investment decision.

[19] The correlation coefficients are estimated via EViews.

	BARCLAYS US AGGREGATE	BOFA ML GLOBAL GVT INDEX	HEDGE CONV ARBITRAGE	HEDGE DEDI SHORT BIAS	HEDGE DISTRESSED	HEDGE EVENT DRVNMSTRT	HEDGE RISK ARBITRAGE	HEDGE EMERG. MARKETS	HEDGE EQUITY MKT.NTL	HEDGE EVENT DRIVEN	HEDGE FXD INC ARBT	HEDGE GLOBAL MACRO	HEDGE FUND	HEDGE LONG/SHORT EQTY	HEDGE MANAGED FUT	MSCI WORLD	HEDGE MULTI-STRATEGY	S&P 500 COMPOSITE
BARCLAYS US AGGREGATE	1.000																	
BOFA ML GLOBAL GVT INDEX	0.551	1.000																
HEDGE CONV ARBITRAGE	-0.282	0.082	1.000															
HEDGE DEDI SHORT BIAS	-0.157	-0.147	-0.396	1.000														
HEDGE DISTRESSED	-0.285	0.103	0.543	-0.505	1.000													
HEDGE EVENT DRVNMSTRT	-0.120	0.157	0.541	-0.575	0.810	1.000												
HEDGE RISK ARBITRAGE	0.109	0.285	0.457	-0.555	0.499	0.689	1.000											
HEDGE EMERG. MARKETS	-0.093	0.071	0.404	-0.407	0.668	0.733	0.555	1.000										
HEDGE EQUITY MKT.NTL	-0.342	0.306	0.545	-0.087	0.386	0.261	0.303	0.346	1.000									
HEDGE EVENT DRIVEN	-0.170	0.152	0.563	-0.579	0.902	0.983	0.674	0.746	0.314	1.000								
HEDGE FXD INC ARBT	-0.366	0.464	0.557	-0.053	0.524	0.456	0.277	0.293	0.756	0.495	1.000							
HEDGE GLOBAL MACRO	-0.346	0.052	0.466	-0.257	0.612	0.680	0.512	0.816	0.627	0.689	0.555	1.000						
HEDGE FUND	-0.252	0.097	0.620	-0.606	0.878	0.898	0.681	0.875	0.477	0.931	0.481	0.801	1.000					
HEDGE LONG/SHORT EQTY	-0.165	0.081	0.570	-0.660	0.847	0.857	0.666	0.883	0.394	0.893	0.343	0.720	0.978	1.000				
HEDGE MANAGED FUT	-0.304	-0.221	0.301	-0.661	0.588	0.585	0.452	0.454	0.125	0.610	0.067	0.340	0.675	0.668	1.000			
MSCI WORLD	-0.039	0.090	0.475	-0.686	0.760	0.780	0.531	0.770	0.170	0.806	0.251	0.510	0.845	0.885	0.651	1.000		
HEDGE MULTI-STRATEGY	-0.332	0.130	0.742	-0.502	0.879	0.839	0.691	0.729	0.549	0.890	0.588	0.745	0.933	0.890	0.531	0.709	1.000	
S&P 500 COMPOSITE	0.073	-0.047	0.262	-0.650	0.494	0.584	0.400	0.509	-0.191	0.579	-0.031	0.228	0.558	0.611	0.585	0.869	0.409	1.000

Figure 2: Pearson correlation coefficients for the asset pairs during the pre-crisis period

Based on the classic Markowitz approach, the portfolio that offers the best possible expected return for the lowest level of risk invests 60.82% on bonds and 39.18% on hedge funds. Additionally, the result that can be derived from charts 15 and 16 is that the inclusion of hedge funds in a portfolio of traditional assets leads to higher expected return and smaller risk (See Appendix B for the Matlab code used for Mean-Variance Optimal Portfolios).

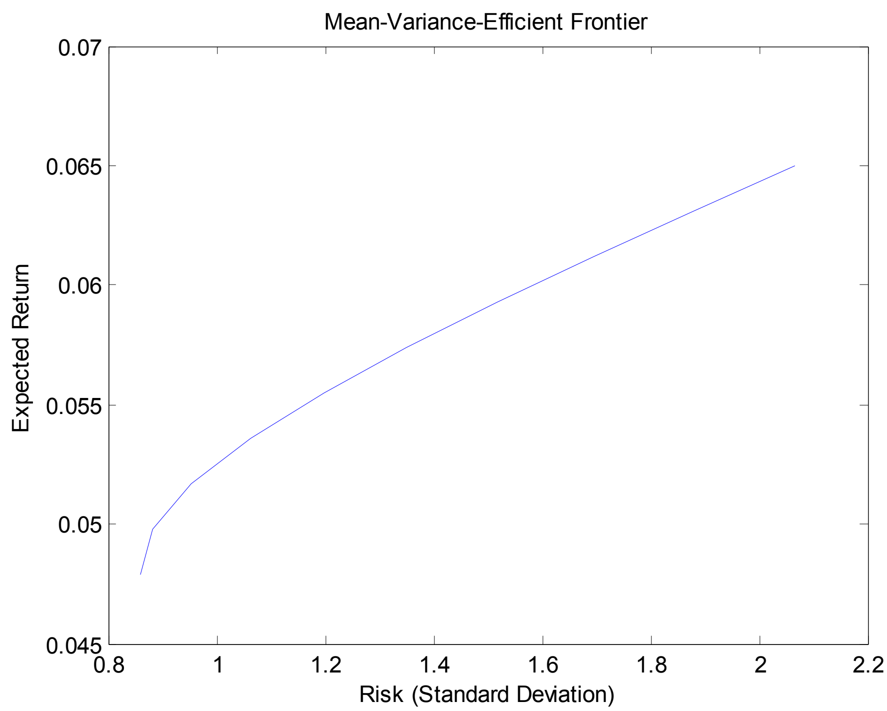

Chart 15: Mean-Variance Efficient Frontier for a bonds-only portfolio

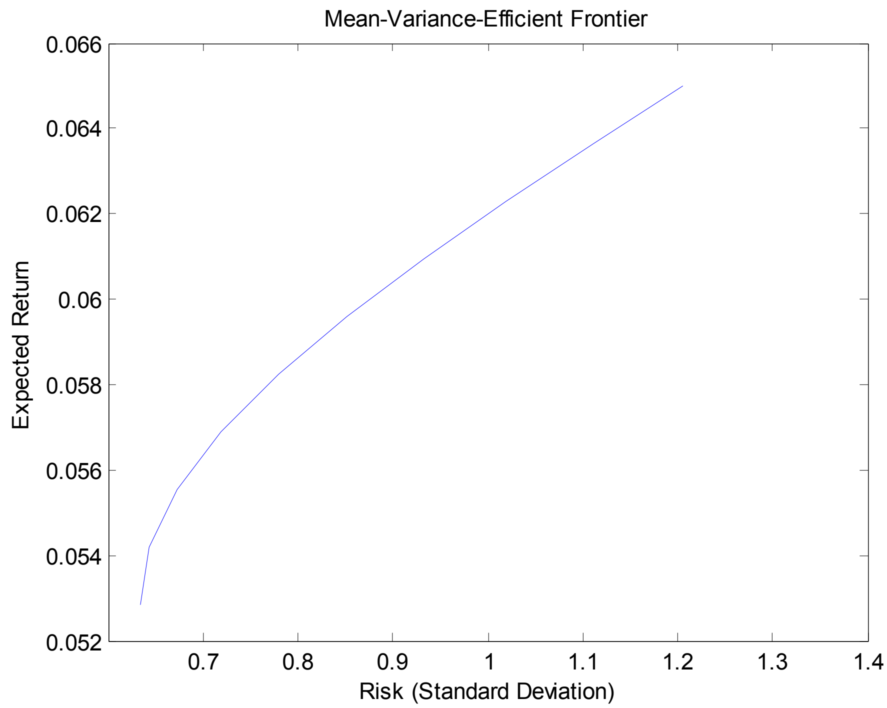

Chart 16: Mean-Variance Efficient Frontier for a portfolio containing hedge funds

Finally, based on the estimation of Value at Risk and Adjusted Modified Value at Risk we examine whether or not the inclusion of hedge funds remains beneficial for the portfolio. The results on table 28 reject this argument due to the fact that when autocorrelation, bias and fat-tails problems are taken into account the portfolio results in lower returns and higher risk. In other words, for the period from January 2005 to January 2007 hedge funds are not considered such an attractive investment decision when autocorrelation, bias and fat-tails problems are taken into consideration. In any case, though, integrating hedge funds in the traditional portfolio is more beneficial than holding a portfolio of only stocks and bonds due to the fact that the traditional portfolio results in negative mean return for this period, as shown in table 29.

	Portfolio	Adjusted Portfolio
Mean Return	0.2485	0.17044
Standard Deviation	0.6332	0.6816
Value at risk	0.7930	
Adjusted Modified Value at Risk		1.0150

Table 28: Portfolio Value at Risk and Adjusted Modified Value at Risk

Ratio	Hedge Fund Portfolio	Traditional Portfolio
Return/Value at risk	0.3134	-0.0136
Return/(Adjusted) Modified Value at Risk	0.1679	-0.0116

Table 29: Risk/Return Ratios

6.2 The Crisis Period

The following figure presents the Pearson correlation coefficients of the hedge fund returns among themselves as well as compared to stock and bond returns during the period from February 2007 to May 2009. It is deduced that hedge funds show small positive or even negative correlation with bond indices whereas the correlation with stock indices can be characterized as medium to large, with the exception of funds using the Dedicated Short Bias and Managed Futures strategy that show negative correlation with stocks. Consequently, a portfolio of bonds and hedge funds seems as a beneficial investment decision.

	BARCLAYS US AGGREGATE	GLOBAL GVT INDEX	HEDGE CONV ARBITRAGE	HEDGE DEDI SHORT BIAS	HEDGE DISTRESSED	HEDGE EVENT DRVNMSTRT	HEDGE RISK ARBITRAGE	HEDGE EMERG. MARKETS	HEDGE EQUITY MKT.NTL	HEDGE EVENT DRIVEN	HEDGE FXD INC ARBT	HEDGE GLOBAL MACRO	HEDGE FUND	LONG/SHORT EQTY	HEDGE MANAGED FUT	MSCI WORLD	HEDGE MULTI-STRATEGY	S&P 500 COMPOSITE
BARCLAYS US AGGREGATE	1																	
BOFA ML GLOBAL GVT INDEX	0.773	1																
HEDGE CONV ARBITRAGE	0.283	-0.032	1															
HEDGE DEDI SHORT BIAS	-0.097	0.064	-0.281	1														
HEDGE DISTRESSED	-0.083	-0.151	0.778	-0.366	1													
HEDGE EVENT DRVNMSTRT	0.017	-0.076	0.785	-0.298	0.890	1												
HEDGE RISK ARBITRAGE	0.375	0.346	0.663	-0.284	0.638	0.661	1											
HEDGE EMERG. MARKETS	0.306	0.226	0.844	-0.408	0.833	0.857	0.793	1										
HEDGE EQUITY MKT.NTL	-0.433	-0.192	0.131	-0.135	0.496	0.261	0.118	0.175	1									
HEDGE EVENT DRIVEN	-0.012	-0.100	0.807	-0.334	0.955	0.985	0.679	0.875	0.353	1								
HEDGE FXD INC ARBT	0.267	0.042	0.885	-0.412	0.789	0.684	0.612	0.823	0.328	0.744	1							
HEDGE GLOBAL MACRO	0.336	0.309	0.733	0.025	0.589	0.668	0.671	0.734	0.006	0.661	0.619	1						
HEDGE FUND	0.073	0.023	0.850	-0.340	0.935	0.933	0.766	0.917	0.405	0.961	0.823	0.752	1					
HEDGE LONG/SHORT EQTY	0.205	0.115	0.801	-0.458	0.842	0.900	0.809	0.921	0.175	0.907	0.745	0.675	0.936	1				
HEDGE MANAGED FUT	-0.127	0.120	-0.105	0.144	-0.030	0.111	0.113	-0.007	-0.127	0.061	-0.177	0.417	0.127	0.109	1			
MSCI WORLD	0.317	0.344	0.483	-0.611	0.612	0.503	0.616	0.669	0.407	0.560	0.593	0.270	0.628	0.686	-0.186	1		
HEDGE MULTI-STRATEGY	0.027	-0.141	0.911	-0.283	0.929	0.904	0.716	0.861	0.395	0.939	0.830	0.683	0.957	0.864	-0.014	0.538	1	
S&P 500 COMPOSITE	0.276	0.306	0.408	-0.582	0.555	0.418	0.532	0.565	0.458	0.482	0.534	0.187	0.545	0.581	-0.217	0.984	0.469	1

Figure 3: Pearson correlation coefficients for the asset pairs during the crisis period

Moreover, the following charts depict the impact of hedge funds on a portfolio of traditional assets based on the classical Markowitz approach. In particular, chart 17 presents the optimization results of a portfolio containing only traditional assets and chart 18 demonstrates the optimization results of a portfolio containing traditional assets and hedge funds. Specifically, the optimal portfolio based on the classical Markowitz approach invests 81.6% on bonds and 18.4% on hedge funds.

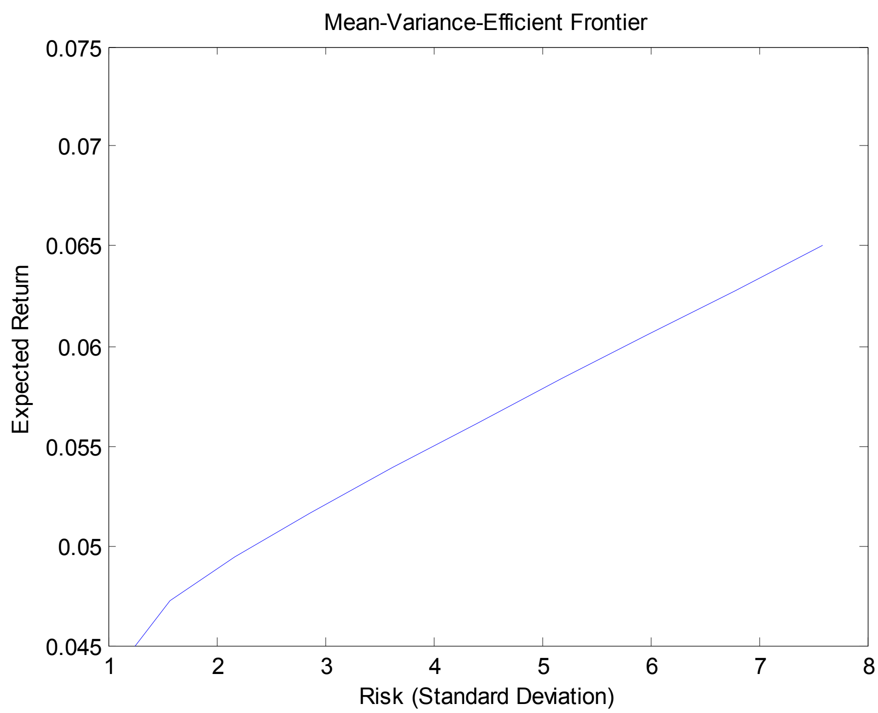

Chart 17: Mean-Variance Efficient Frontier for a bonds-only portfolio

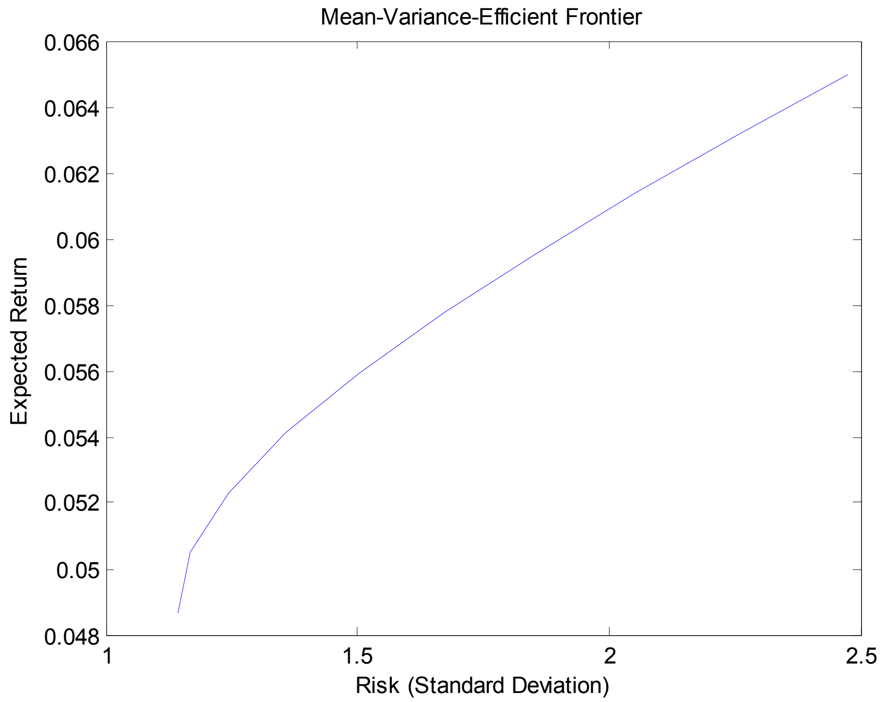

Chart 18: Mean-Variance Efficient Frontier for a portfolio containing hedge funds

Comparing the case with and without hedge funds, we see a significant improvement of portfolio performance with an increase of expected return and a reduction of risk when hedge funds are added to the portfolio (See Appendix B for the Matlab code used for Mean-Variance Optimal Portfolios).

The next step is to confirm whether or not hedge fund beneficial impact on a portfolio remains when autocorrelation, bias and fat-tails are taken into consideration. The following table presents that the adjusted portfolio, where these three problems are taken into account, obtains lower return and higher risk. In terms of risk/return trade off based on Value at Risk and on Adjusted Modified Value at Risk, this ratio is higher when it is calculated on the basis of Value at Risk. In other words, during the crisis period hedge funds lose their attractiveness when autocorrelation, bias and fat-tails problems are considered in the portfolio evaluation process. Furthermore, the traditional portfolio which refers to a bonds-only portfolio results in higher return/risk ratios on Value at Risk and on Modified Value at Risk basis, as it is presented in table 31.

	Portfolio	Adjusted Portfolio
Mean	-0.0060	-0.0978
Standard Deviation	1.1436	1.5426
Value at risk	1.8870	
Adjusted Modified Value at Risk		1.6418

Table 30: Portfolio Value at Risk and Adjusted Modified Value at Risk

Ratio	Hedge Fund Portfolio	Traditional Portfolio
Return/Value at risk	-0.0032	0.0218
Return/(Adjusted) Modified Value at Risk	-0.0596	0.0254

Table 31: Risk/Return Ratios

6.3 The Post-Credit Crisis Period

To start the analysis for the period from June 2009 to October 2011, Pearson's correlation coefficients are presented to the following figure for all the asset pairs under examination. As shown in this figure, all hedge funds show small negatively or positively correlated returns with bonds. However, specific hedge fund indices, such as Global Macro, Managed Futures and Equity Market Neutral indices, exhibit a relatively high level of correlation with BofA Merill Lynch Global Government Bond Index. Additionally, hedge funds indices show large positive correlations with stocks and among themselves. Tentatively, a promising portfolio seems to include bonds and hedge funds.

	BARCLAYS US AGGREGATE	BOFA ML GLOBAL GVT INDEX	HEDGE CONV ARBITRAGE	HEDGE DEDI SHORT BIAS	HEDGE DISTRESSED	HEDGE EVENT DRVNMSTRT	HEDGE RISK ARBITRAGE	HEDGE EMERG. MARKETS	HEDGE EQUITY MKT.NTL	HEDGE EVENT DRIVEN	HEDGE FXD INC ARBT	HEDGE GLOBAL MACRO	HEDGE FUND	HEDGE LONG/SHORT EQTY	HEDGE MANAGED FUT	MSCI WORLD	HEDGE MULTI-STRATEGY	S&P 500 COMPOSITE
BARCLAYS US AGGREGATE	1																	
BOFA ML GLOBAL GVT INDEX	0.678	1.000																
HEDGE CONV ARBITRAGE	-0.037	0.114	1.000															
HEDGE DEDI SHORT BIAS	0.331	-0.056	-0.598	1.000														
HEDGE DISTRESSED	-0.251	0.062	0.753	-0.822	1.000													
HEDGE EVENT DRVNMSTRT	-0.253	0.133	0.713	-0.870	0.945	1.000												
HEDGE RISK ARBITRAGE	-0.016	0.501	0.598	-0.699	0.705	0.734	1.000											
HEDGE EMERG. MARKETS	-0.125	0.311	0.640	-0.793	0.785	0.811	0.755	1.000										
HEDGE EQUITY MKT.NTL	0.026	0.551	0.478	-0.685	0.614	0.664	0.828	0.713	1.000									
HEDGE EVENT DRIVEN	-0.253	0.112	0.735	-0.862	0.975	0.994	0.735	0.813	0.654	1.000								
HEDGE FXD INC ARBT	0.147	0.283	0.869	-0.493	0.719	0.631	0.585	0.605	0.495	0.669	1.000							
HEDGE GLOBAL MACRO	0.424	0.678	0.126	-0.326	0.240	0.357	0.418	0.407	0.479	0.321	0.319	1.000						
HEDGE FUND	-0.113	0.334	0.699	-0.879	0.881	0.940	0.799	0.893	0.767	0.931	0.665	0.575	1.000					
HEDGE LONG/SHORT EQTY	-0.279	0.200	0.648	-0.943	0.856	0.925	0.776	0.886	0.726	0.911	0.545	0.429	0.963	1.000				
HEDGE MANAGED FUT	0.250	0.574	0.156	-0.295	0.249	0.389	0.392	0.371	0.441	0.344	0.213	0.809	0.569	0.450	1.000			
MSCI WORLD	-0.281	0.314	0.627	-0.811	0.747	0.799	0.773	0.833	0.753	0.789	0.567	0.362	0.853	0.886	0.365	1.000		
HEDGE MULTI-STRATEGY	-0.170	0.223	0.833	-0.846	0.896	0.905	0.756	0.871	0.743	0.913	0.748	0.335	0.925	0.904	0.313	0.830	1.000	
S&P 500 COMPOSITE	-0.375	0.189	0.585	-0.828	0.744	0.781	0.706	0.798	0.697	0.776	0.534	0.322	0.820	0.866	0.296	0.977	0.807	1.000

Figure 4: Pearson correlation coefficients for the asset pairs during the post-credit crisis period

The results from the Mean-Variance optimization indeed suggest a portfolio that contains mainly bonds and hedge funds. Specifically, the optimal portfolio is constructed to invest 79.02% in bonds, 2% in stocks and 18.36% in hedge funds (See Appendix B for the Matlab code used for Mean-Variance Optimal Portfolios). Moreover, the comparison of the following charts confirms the argument that integrating hedge funds in a portfolio of traditional investments results in a reduction of risk and an improvement of portfolio performance.

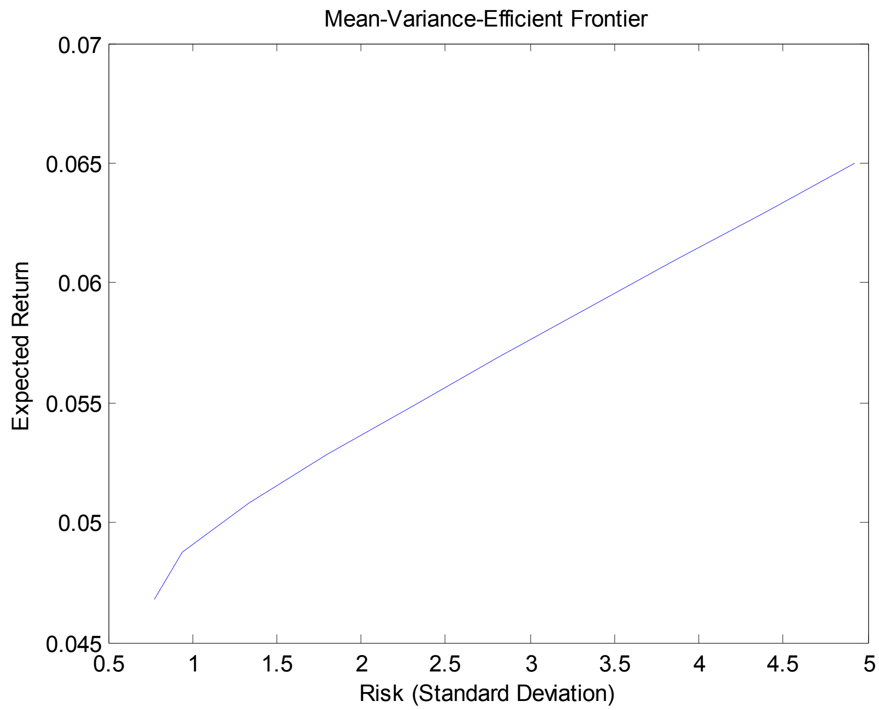

Chart 19: Mean-Variance Efficient Frontier for a portfolio containing bonds and stocks

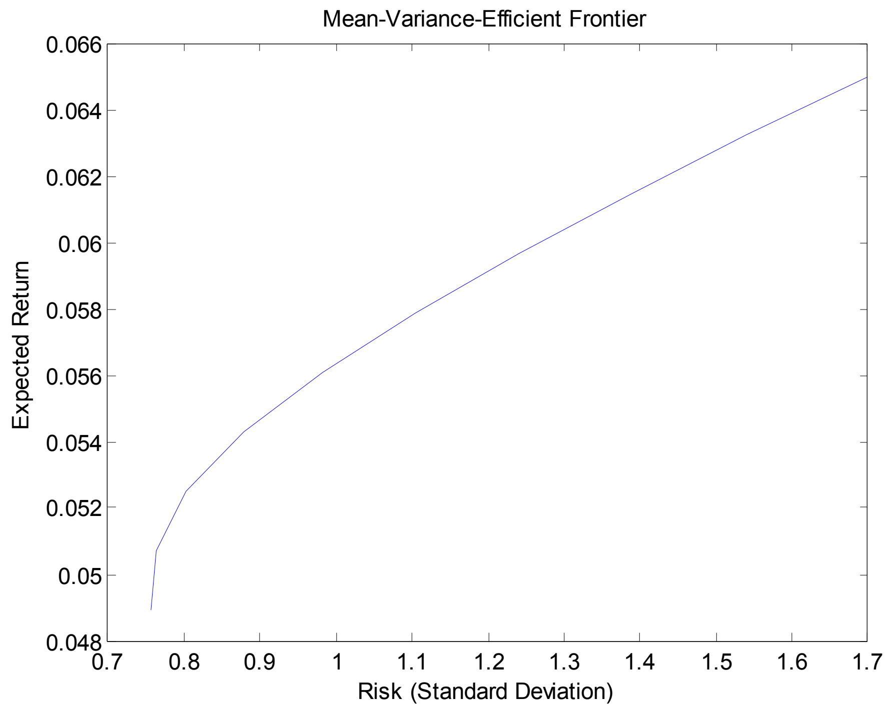

Chart 20: Mean-Variance Efficient Frontier for a portfolio containing hedge funds

On the contrary, the results of Value at Risk and Adjusted Modified Value at Risk, shown in table 32, indicate that hedge funds' characteristics of autocorrelation, bias and fat-tails render the portfolio less attractive. In this case, the expected return of the portfolio is reduced while portfolio's risk increases as it can be deduced from the comparison between Value at Risk and Adjusted Modified Value at Risk. In addition to this, when we compare the portfolio containing hedge funds with the traditional portfolio on terms of return-to-Value at Risk ratio, the result is that the hedge fund portfolio is a better investment choice than the traditional portfolio. However, on terms of return-to-Modified Value at Risk ratio, the traditional portfolio is considered the best choice. These results are shown in table 33.

	Portfolio	Adjusted Portfolio
Mean Return	0.3563	0.2642
Standard Deviation	0.7567	1.1619
Value at risk	0.8883	
Adjusted Modified Value at Risk		1.7110

Table 32: Portfolio Value at Risk and Adjusted Modified Value at Risk

Ratio	Hedge Fund Portfolio	Traditional Portfolio
Return/Value at risk	0.4011	0.3246
Return/(Adjusted) Modified Value at Risk	0.1544	0.3317

Table 33: Risk/Return Ratios

CHAPTER 7

Conclusions

The main objective of this thesis was to accurately measure hedge fund performance during different time intervals with emphasis on the recent global financial crisis. The identification of the financial crisis was a crucial task because through this procedure our sample was specifically defined. Furthermore, we aimed to investigate hedge fund performance as standalone assets and as part of a portfolio. A summary of conclusions will be tabulated here with respect to the aforementioned objectives and the apposite chapters of this thesis.

The findings of literature that hedge funds are subject to autocorrelation, bias and tail risk are confirmed in our analysis. These problems were examined through statistical measures and based on literature. The main result of our analysis is that care must be taken in measuring investment vehicles such as hedge funds because there are many implications that render this objective a challenging task. Under the classical performance measurement context, hedge funds are found to be a more appealing investment decision than traditional assets. However, when the aforementioned problems are taken into consideration, previous results are invalidated because hedge fund performance is proved to be inadequate. This result is aggravated in crucial periods of financial distress such as the global financial crisis of 2007-2009.

With reference to the last chapter, a methodology was followed for comparing both qualitatively and quantitatively portfolios that include only traditional assets (bonds, stocks) and portfolios that include hedge funds as well. A key step to this comparison is to account for the autocorrelation, bias and fat-tails problems. Adjusted Modified Value at Risk is especially suited for this task as this measure can alleviate the effects of the aforementioned problems and improve overall conclusions. All things considered, the integration of hedge funds in a portfolio of traditional assets can potentially lead to the opposite result as in the case of the recent global financial crisis. Specifically during this period a portfolio of traditional assets and hedge funds obtained a negative expected return and a high level of risk while a bonds-only portfolio delivered better results. On the other hand, for the period from January 2005 to January 2007 integrating hedge funds in a traditional portfolio proved to be a prosperous investment decision even though hedge funds lost a proportion of their attractiveness when autocorrelation, bias and fat-tails were taken into account. This feature was also present to the portfolio analysis of the period from June 2009 to October 2011. Under the Value at Risk framework, the portfolio that contains hedge funds and traditional assets is suggested as the optimal decision but under the Adjusted Modified Value at Risk framework the traditional is undoubtedly the optimal investment choice.

To conclude, the comparative analysis in the case of hedge funds is a good example that erroneous hypotheses easily lead to naïve and costly results. Therefore, it is important to examine potential risks as well as advantages that an investment incurs in order to make this investment a prosperous one.

APPENDIX A

Correlograms

The Pre-Crisis Period

- Correlogram of Barclays US Aggregate Bond Index returns

Sample: 2005M01 2007M01
Included observations: 24

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.067	0.067	0.1224	0.726
		2	-0.163	-0.168	0.8753	0.646

- Correlogram of BofA Global Government Bond Index returns

Sample: 2005M01 2007M01
Included observations: 24

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.189	-0.189	0.9703	0.325
		2	-0.161	-0.204	1.7091	0.425

- Correlogram of Convertible Arbitrage Index returns

Sample: 2005M01 2007M01
Included observations: 24

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.615	0.615	10.256	0.001
		2	0.204	-0.280	11.431	0.003

- Correlogram of Dedicated Short Bias Index returns

Sample: 2005M01 2007M01
Included observations: 24

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.358	0.358	3.4862	0.062
		2	0.104	-0.028	3.7924	0.150

- Correlogram of Distressed Securities Index returns

Sample: 2005M01 2007M01
Included observations: 24

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.021	0.021	0.0122	0.912
		2	0.092	0.092	0.2537	0.881

- Correlogram of Event Driven Multi-Strategy Index returns

Sample: 2005M01 2007M01
Included observations: 24

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.017	0.017	0.0075	0.931
		2	-0.028	-0.029	0.0305	0.985

- Correlogram of Risk Arbitrage Index returns

Sample: 2005M01 2007M01
Included observations: 24

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.027	-0.027	0.0202	0.887
		2	-0.040	-0.041	0.0666	0.967

- Correlogram of Emerging Markets Index returns

Sample: 2005M01 2007M01
Included observations: 24

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.103	-0.103	0.2858	0.593
		2	-0.056	-0.067	0.3739	0.830

- Correlogram of Equity Market Neutral Index returns

Sample: 2005M01 2007M01
Included observations: 24

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.338	0.338	3.0982	0.078
		2	0.011	-0.116	3.1018	0.212

- Correlogram of Event Driven Index returns

Sample: 2005M01 2007M01
Included observations: 24

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.026	0.026	0.0190	0.890
		2	-0.025	-0.025	0.0361	0.982

- Correlogram of Fixed Income Arbitrage Index returns

Sample: 2005M01 2007M01
Included observations: 24

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.338	0.338	3.0951	0.079
		2	-0.154	-0.303	3.7680	0.152

- Correlogram of Global Macro Index returns

Sample: 2005M01 2007M01
Included observations: 24

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.021	-0.021	0.0122	0.912
		2	-0.024	-0.025	0.0287	0.986

- Correlogram of Hedge Fund Index returns

Sample: 2005M01 2007M01
Included observations: 24

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.064	0.064	0.1117	0.738
		2	-0.010	-0.014	0.1146	0.944

- Correlogram of Long/Short Equity Index returns

Sample: 2005M01 2007M01
Included observations: 24

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.112	0.112	0.3406	0.560
		2	-0.028	-0.041	0.3626	0.834

- Correlogram of Managed Futures Index returns

Sample: 2005M01 2007M01
Included observations: 24

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.146	-0.146	0.5799	0.446
		2	0.065	0.045	0.7000	0.705

- Correlogram of MSCI World Index returns

Sample: 2005M01 2007M01
Included observations: 24

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.153	-0.153	0.6376	0.425
		2	0.210	0.191	1.8897	0.389

- Correlogram of Multi-strategy Index returns

Sample: 2005M01 2007M01
Included observations: 24

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.309	0.309	2.5957	0.107
		2	-0.011	-0.118	2.5993	0.273

- Correlogram of S&P 500 Index returns

Sample: 2005M01 2007M01
Included observations: 24

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.319	-0.319	2.7555	0.097
		2	0.316	0.239	5.5963	0.061

The Crisis Period

- Correlogram of Barclays US Aggregate Bond Index returns

Sample: 2007M02 2009M05
Included observations: 27

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.046	0.046	0.0629	0.802
		2	-0.378	-0.381	4.5329	0.104

- Correlogram of BofA Global Government Bond Index returns

Sample: 2007M02 2009M05
Included observations: 27

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.056	0.056	0.0961	0.757
		2	-0.319	-0.323	3.2871	0.193

- Correlogram of Convertible Arbitrage Index returns

Sample: 2007M02 2009M05
Included observations: 27

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.435	0.435	5.6952	0.017
		2	0.071	-0.146	5.8515	0.054

- Correlogram of Dedicated Short Bias Index returns

Sample: 2007M02 2009M05
Included observations: 27

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.012	-0.012	0.0046	0.946
		2	-0.378	-0.378	4.4728	0.107

- Correlogram of Distressed Securities Index returns

Sample: 2007M02 2009M05
Included observations: 27

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.567	0.567	9.6935	0.002
		2	0.352	0.044	13.573	0.001

- Correlogram of Event Driven Multi-Strategy Index returns

Sample: 2007M02 2009M05
Included observations: 27

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.244	0.244	1.7931	0.181
		2	0.268	0.221	4.0392	0.133

- Correlogram of Risk Arbitrage Index returns

Sample: 2007M02 2009M05
Included observations: 27

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.485	0.485	7.0884	0.008
		2	-0.007	-0.317	7.0901	0.029

- Correlogram of Emerging Markets Index returns

Sample: 2007M02 2009M05
Included observations: 27

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.444	0.444	5.9464	0.015
		2	0.206	0.011	7.2770	0.026

- Correlogram of Equity Market Neutral Index returns

Sample: 2007M02 2009M05
Included observations: 27

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.007	0.007	0.0015	0.969
		2	-0.027	-0.027	0.0239	0.988

- Correlogram of Event Driven Index returns

Sample: 2007M02 2009M05
Included observations: 27

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.377	0.377	4.2693	0.039
		2	0.302	0.186	7.1220	0.028

- Correlogram of Fixed Income Arbitrage Index returns

Sample: 2007M02 2009M05
Included observations: 27

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.499	0.499	7.4879	0.006
		2	0.054	-0.258	7.5807	0.023

- Correlogram of Global Macro Index returns

Sample: 2007M02 2009M05
Included observations: 27

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.413	0.413	5.1406	0.023
		2	-0.027	-0.238	5.1635	0.076

- Correlogram of Hedge Fund Index returns

Sample: 2007M02 2009M05
Included observations: 27

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.511	0.511	7.8613	0.005
		2	0.254	-0.009	9.8828	0.007

- Correlogram of Long/Short Equity Index returns

Sample: 2007M02 2009M05
Included observations: 27

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.401	0.401	4.8369	0.028
		2	0.156	-0.006	5.5945	0.061

- Correlogram of Managed Futures Index returns

Sample: 2007M02 2009M05
Included observations: 27

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.221	0.221	1.4684	0.226
		2	-0.516	-0.594	9.8128	0.007

- Correlogram of MSCI World Index returns

Sample: 2007M02 2009M05
Included observations: 27

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.189	0.189	1.0810	0.298
		2	-0.306	-0.355	4.0146	0.134

- Correlogram of Multi-strategy Index returns

Sample: 2007M02 2009M05
Included observations: 27

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.551	0.551	9.1441	0.002
		2	0.251	-0.076	11.113	0.004

- Correlogram of S&P 500 Index returns

Sample: 2007M02 2009M05
Included observations: 27

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.094	0.094	0.2658	0.606
		2	-0.360	-0.372	4.3335	0.115

The Post-Credit Crisis Period

- Correlogram of Barclays US Aggregate Bond Index returns

Sample: 2009M06 2011M10
Included observations: 28

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.028	0.028	0.0251	0.874
		2	0.164	0.163	0.8915	0.640

- Correlogram of BofA Global Government Bond Index returns

Sample: 2009M06 2011M10
Included observations: 28

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.107	-0.107	0.3579	0.550
		2	-0.029	-0.041	0.3854	0.825

- Correlogram of Convertible Arbitrage Index returns

Sample: 2009M06 2011M10
Included observations: 28

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.523	0.523	8.5236	0.004
		2	0.216	-0.080	10.029	0.007

- Correlogram of Dedicated Short Bias Index returns

Sample: 2009M06 2011M10
Included observations: 28

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.144	0.144	0.6419	0.423
		2	0.158	0.141	1.4534	0.483

- Correlogram of Distressed Securities Index returns

Sample: 2009M06 2011M10
Included observations: 28

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.443	0.443	6.0936	0.014
		2	0.175	-0.026	7.0825	0.029

- Correlogram of Event Driven Multi-Strategy Index returns

Sample: 2009M06 2011M10
Included observations: 28

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.426	0.426	5.6531	0.017
		2	0.208	0.033	7.0576	0.029

- Correlogram of Risk Arbitrage Index returns

Sample: 2009M06 2011M10
Included observations: 28

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.157	0.157	0.7664	0.381
		2	0.035	0.010	0.8050	0.669

- Correlogram of Emerging Markets Index returns

Sample: 2009M06 2011M10
Included observations: 28

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.149	0.149	0.6888	0.407
		2	-0.128	-0.154	1.2199	0.543

- Correlogram of Equity Market Neutral Index returns

Sample: 2009M06 2011M10
Included observations: 28

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.040	-0.040	0.0500	0.823
		2	-0.126	-0.128	0.5648	0.754

- Correlogram of Event Driven Index returns

Sample: 2009M06 2011M10
Included observations: 28

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.441	0.441	6.0476	0.014
		2	0.203	0.011	7.3828	0.025

- Correlogram of Fixed Income Arbitrage Index returns

Sample: 2009M06 2011M10
Included observations: 28

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.409	0.409	5.2120	0.022
		2	0.350	0.219	9.1738	0.010

- Correlogram of Global Macro Index returns

Sample: 2009M06 2011M10
Included observations: 28

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.413	-0.413	5.3007	0.021
		2	0.089	-0.098	5.5567	0.062

- Correlogram of Hedge Fund Index returns

Sample: 2009M06 2011M10
Included observations: 28

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.191	0.191	1.1404	0.286
		2	0.081	0.046	1.3515	0.509

- Correlogram of Long/Short Equity Index returns

Sample: 2009M06 2011M10
Included observations: 28

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.204	0.204	1.2996	0.254
		2	0.091	0.051	1.5654	0.457

- Correlogram of Managed Futures Index returns

Sample: 2009M06 2011M10
Included observations: 28

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.321	-0.321	3.2119	0.073
		2	0.003	-0.112	3.2122	0.201

- Correlogram of MSCI World Index returns

Sample: 2009M06 2011M10
Included observations: 28

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.053	0.053	0.0867	0.768
		2	-0.063	-0.066	0.2135	0.899

- Correlogram of Multi-strategy Index returns

Sample: 2009M06 2011M10
Included observations: 28

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.375	0.375	4.3729	0.037
		2	0.141	0.001	5.0151	0.081

- Correlogram of S&P 500 Index returns

Sample: 2009M06 2011M10
Included observations: 28

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.039	0.039	0.0462	0.830
		2	-0.050	-0.051	0.1258	0.939

APPENDIX B

Matlab Code for Mean-Variance Optimal Portfolios

```
clear all;

data=xlsread('portfolio.xls');
eret=mean(data);
covmat=cov(data);
f=[];
A=[];
B=[];
Aeq=ones(1,3);
beq=1;

weights=quadprog(covmat,f,A,B,Aeq,beq,zeros(3,1));
er=[0.045;0.055;0.065];


data1=xlsread('portfolio.xls','portfolio','b3:c29');
eret1=mean(data1);
covmat1=cov(data1);
f1=[];
A1=[];
B1=[];
Aeq1=ones(1,2);
beq1=1;

weights1=quadprog(covmat1,f1,A1,B1,Aeq1,beq1,zeros(2,1));
er1=[0.045;0.065];

frontcon(er,covmat);
grid off;
hold on;
frontcon(er1,covmat1);
grid off;
hold off;
```

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