ANALYSING NONLINEAR SYSTEMATIC RISK EXPOSURES IN HEDGE FUNDS

By

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Notice 1

Notice 2

Dedication

This work is dedicated to my family.

Declaration

This thesis contains no material that has been accepted for the award of any other degree or diploma in any university or other institution. To the best of my ability and belief, this thesis contains no material previously published or written by another person, except where due reference is made in the text.

Signed _____________________ Date____________________

Mikhail Tupitsyn

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Research Publications

The author has published two research works related to the topic of this thesis. The first publication is a book chapter:

Tupitsyn, M., & Lajbcygier, P. (2013). Hedge Funds: Replication and Nonlinearities. In H. K. Baker & G. Filbeck (Eds.), Alternative Investments: Instruments, Performance, Benchmarks, and Strategies (pp. 541-566). Hoboken, NJ: John Wiley & Sons.

It contains a part of the literature review from Chapter 3, the methodology related to Generalized Additive Models from Chapter 5 and the preliminary version of empirical results from Chapter 8.

The second publication co-authored with other researchers is a journal paper:

Do, V., Faff, R. W., Lajbcygier, P., Veeraraghavan, M., & Tupitsyn, M. (2014, forthcoming). Factors Affecting the Birth of and Fund Flows into CTAs. Australian Journal of Management.

This study explores in detail the characteristics and flow-performance relationship in the Managed Futures/CTA style of hedge funds. It has contributed to the discussion related to specific features and performance of the CTA style in this thesis.

Abstract

Using a nonparametric statistical methodology this thesis analyses nonlinear risk exposures in portfolios and individual hedge funds. At the portfolio level an out-of-sample evidence of nonlinearities is documented in most of the styles; however, nonlinear features are found to be more pronounced in arbitrage related hedge fund styles, rather than in directional styles. A nonparametric approach based on a Generalized Additive Model (GAM) captures nonlinearities better than the widely accepted seven-factor Fung and Hsieh (2004b) model and outperforms linear multi-factor models in out-of-sample tests. At the fund level, one-fifth of funds exhibit significant nonlinearities detected using GAMs. In addition, individual funds with nonlinear risk exposures have on average lower raw and risk-adjusted returns and higher left tail risk than funds with only linear risk exposures. Thus, nonlinearities do not signal skill among fund managers. Finally, linear and nonparametric models are employed to replicate broad hedge fund benchmarks as well as investable hedge fund indices. It is found that the nonparametric model better tracks hedge fund benchmarks than the linear model, confirming the importance of nonlinearities.

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List of Abbreviations

ABS	Asset-Based Style analysis
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
CA	Convertible Arbitrage
CTA	Commodity Trading Advisor
DS	Distressed/Restructuring
DSB	Dedicated Short Bias
ED	Event Driven
EH	Equity Hedge
EM	Emerging Markets
EMN	Equity Market Neutral
ES	Expected Shortfall
ETF	Exchange Traded Fund
EW	Equal Weighted
FH7	Seven factors of Fung and Hsieh (2004b); the seven-factor model of Fung and Hsieh (2004b)
FIA	Fixed Income Arbitrage
FoF	Fund of Funds
GAM	Generalized Additive Model
GAML6	GAM using Loess smoothers with bandwidth 1 and HL6 factors
GAML6-05	GAM using Loess smoothers with bandwidth 0.5 and HL6 factors
GAML6-075	GAM using Loess smoothers with bandwidth 0.75 and HL6 factors
GAMS6	GAM using Splines and HL6 factors
GAMS14	GAM using Splines and 14 factors
GM	Global Macro

HFC	Hedge Fund Composite
HFR	Hedge Fund Research database
HFRI	Non-investable HFR indices
HFRX	Investable HFR indices
HL6	Six factors of Hasanhodzic and Lo (2007); the six-factor model of Hasanhodzic and Lo (2007)
LSE	Long-Short Equity
M	Macro
MA	Merger Arbitrage
MAE	Mean Absolute Error
MARS	Multivariate Adaptive Regression Splines
MARS6	Multivariate Adaptive Regression Splines Model with HL6 factors
MARS14	Multivariate Adaptive Regression Splines Model with 14 factors
MF	Managed Futures
MS	Multi-Strategy
PMTS	Primitive Market Timing Strategy
PTFS	Primitive Trend Following Strategy
RGAMS6	Robust GAM using Spline smoothers and HL6 factors
RGAMS14	Robust GAM using Spline smoothers and 14 factors
RLM6	Robust Linear Model – median regression with HL6 factors
RLM14	Robust Linear Model – median regression with 14 factors
RMSE	Root-Mean Squared Error
RVA	Relative Value Arbitrage
SGAML14	Stepwise GAM using Loess smoothers with bandwidth 1 and 14 factors
SGAML14-05	Stepwise GAM using Loess smoothers with bandwidth 0.5 and 14 factors
SGAML14-075	Stepwise GAM using Loess smoothers with bandwidth 0.75 and 14 factors
SLM14	Stepwise Linear Model with 14 factors
TASS	Tremont Advisory Shareholder Services database

VaR	Value at Risk
14 factors	Extended set comprising of HL6 factors and other 8 factors

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Chapter 1 Introduction

1.1 Problem Statement

Over the last two decades the hedge fund industry has grown tremendously. The number of funds and their assets under management (AUM) has increased 20-fold from some 530 funds and $50 billion AUM in 1990[1] to more than 10,000 funds and $2.8 trillion in 2014[2]. The largest portion of these new funds has flowed from institutional investors including pension funds, endowment funds and sovereign wealth funds. The inflow of institutional money to alternative investments, and hedge funds in particular, has occurred because investors seek to enhance yields in low interest rate environment. The main allure of hedge funds for investors is both the promise of absolute returns and also diversification to traditional equities and bonds portfolios.

Despite the dramatic growth of the industry, the debate about the added value of hedge funds is still unresolved and ongoing. The crucial question is whether hedge funds generate profits from alpha, i.e. fund manager skill, or beta, i.e. systematic risk premium. Traditional asset pricing models such as the Capital Asset Pricing Model (CAPM) (Lintner, 1965; Mossin, 1966; Sharpe, 1964; Treynor, 1961, 1962) and a multi-factor linear model (Sharpe, 1992) are not suited well to analyse hedge fund returns, because they do not account for nonlinear

[1] HFR, "Investors Return to Hedge Fund Industry as New Model", press release, Hedge Fund Research (20 January 2010).

[2] HFR, "Hedge Fund Capital Surges To New Milestone On Strong 2Q inflows", press release, Hedge Fund Research (18 July 2014).

risk exposures of hedge funds. Hedge funds' trading strategies are dynamic in nature and may involve financial securities with nonlinear payoffs such as options. In contrast to traditional buy-and-hold strategies which generate linear exposures to systematic risk as expressed by the Security Market Line (SLM) hedge funds' trading strategies lead to a nonlinear relationship between the risk and expected return (Agarwal & Naik, 2004; Fung & Hsieh, 1997a, 2001; Mitchell & Pulvino, 2001). These nonlinear strategies do not conform to the assumptions underlying traditional asset pricing models. That is why linear models might lead to biased results for hedge funds.

Accordingly, the aim of this thesis is to perform an examination and assessment of nonlinear systematic risk exposures in hedge funds. Towards this aim the present study focuses on three main areas of investigation. Firstly, this thesis proposes a nonparametric approach to study nonlinear risk exposures in portfolios of hedge funds grouped by fund style. Several nonparametric models, free from functional specification constraints, are developed and applied to explore nonlinear risk-return patterns. Rigorous out-of-sample statistical tests are performed to document the evidence of nonlinearities at portfolio level and compare nonparametric models with traditional linear multi-factor models.

Secondly, this study performs an assessment of nonlinear trading strategies in individual funds. The analysis at the fund level is conducted in order to evaluate managers with different trading approaches, i.e. those who engage in complex dynamic trading strategies with nonlinear risk exposures, and those who follow traditional buy-and-hold like strategies with consequent linear risk-return profiles. Given that hedge funds charge fees much higher than other traditional funds, it is crucial for investors to know whether hedge funds' complex strategies generate positive value over and above standard risk exposures.

Finally, this thesis validates the significance of nonlinear features in risk exposures of hedge funds in the context of passive hedge fund replication. Based on the evidence that considerable part of hedge funds' returns stems from systematic risk premium several studies have attempted to replicate hedge funds' linear beta in a passive way (Hasanhodzic & Lo, 2007; Jaeger & Wagner, 2005). This study extends the literature as it applies nonparametric models to replicate linear and nonlinear risk exposures. By comparing linear and nonlinear passive hedge fund clones it is possible to gauge the importance of the linear and nonlinear systematic risk premium for hedge funds.

The next section discusses more closely contributions of the thesis to the hedge fund literature and relevant implications to practitioners.

1.2 Contributions

Firstly, this thesis provides robust statistical evidence of nonlinearities in risk exposures of hedge fund style portfolios. When modeling nonlinearities the problem of over-fitting the data is of serious concern. As noted by Fung and Hsieh (2004b), a standard way to gauge the usefulness of a model is to carry out an out-of-sample test. From this point of view nonlinear patterns documented so far in the literature lack statistical support, because most of the studies are either limited to an in-sample analysis or fail in out-of-sample tests (Amenc, Martellini, Meyfredi, & Ziemann, 2010). It is not clear whether poor out-of-sample performance of existing models is due to the model misspecification or weak nonlinear effects. This study clarifies the issue by performing an out-of-sample analysis of proposed nonparametric models. The results provide strong statistical evidence of nonlinearities in hedge fund portfolios.

Secondly, this study contributes to the literature on hedge fund performance evaluation. The extant literature documents a number of nonlinear patterns, but provides little clue as to whether returns due to asymmetric risk exposures should be attributed to fund manager's alpha or alternative beta. In theory nonlinear patterns in risk exposures may appear due to both trading strategies with systematic risk, such as strategies involving derivatives with nonlinear payoffs, and alpha generating trading strategies, e.g. market timing strategies. The question about the sources of nonlinearities is important because investors should not be paying high hedge fund fees for mutual fund like strategies whose performance is due to passive risk exposures. To address this question this study performs a peer-group analysis of funds with nonlinear risk exposures, funds with only linear risk exposures, and market-neutral funds. No other study has performed such an analysis yet. The results indicate that nonlinearities do not provide a signal of fund manager skill. On the contrary, there is evidence of excess tail risk and weaker relative performance of nonlinear funds.

Thirdly, the thesis seeks to understand significance of nonlinearities in hedge fund style portfolios from an economic perspective. Hedge fund style indices represent equal- or value-weighted portfolios of funds following similar trading strategies. Although there is evidence suggesting statistical significance of nonlinearities in driving style returns, little research has focused on economic evaluation of the magnitude of nonlinear effects in hedge fund strategies. This thesis applies the idea of passive hedge fund replication to assess the economic importance of nonlinearities. During the previous decade, there was considerable interest in academic hedge fund pricing models amongst financial practitioners who enhanced a number of these models to create commercial products known as hedge fund clones or replicators[3]. Hedge fund clones are designed as passive trading strategies involving only liquid exchange traded securities which aim to track returns of broad hedge fund benchmarks. Hedge fund replication provides a suitable context to test the significance of nonlinearities from a practical perspective. If nonlinear effects are of a sizeable magnitude relative to linear risk exposures, then nonlinear hedge fund replicators would be expected to be more accurate in tracking hedge fund benchmarks than clones based on existing linear models. This is the first attempt in academic literature to investigate potential characteristics of nonlinear clones.

Another important novelty pertaining to replication of hedge funds' systematic risk exposures is related to the choice of hedge fund benchmarks. Extant academic studies have mostly focused on replication of broad hedge fund style indices, which by construction are not investable portfolios, since they include many funds closed to new investments (Giamouridis & Paterlini, 2010; Hasanhodzic & Lo, 2007). In the TASS hedge fund database only 14% of funds were open as of 2010[4]. In this study, replication is carried out for both non-investable indices and investable indices. Investable indices comprise a subset of funds open to new investments. It is observed that hedge fund replicators are no different statistically from non-investable style benchmarks in terms of raw and risk-adjusted returns, although on average they underperform indices. On the other hand, when compared with investable indices replicators demonstrate superior absolute and risk-adjusted performance. These results are very important from a practical perspective as they show that hedge fund

[3] See articles: Liinanki, C. "Investors learn to harvest hedge fund return sources without high fees", *The Financial Times*, April 22, 2012; Haslett, W. "Get a grip on hedge fund replication", *The Financial Times*, October 3 2010

[44] Author's calculation

replicators provide a better alternative for investors seeking a broad exposure to hedge funds, than existing investable indices.

Overall the thesis contributes to the hedge fund literature and its findings will be of interest to financial practitioners and hedge fund investors.

1.3 Structure

The thesis is divided into nine chapters. Following this introduction, brief background details on hedge funds are provided in Chapter 2. The literature review in Chapter 3 explores the current state of research on hedge funds' nonlinear risk exposures and identifies research gaps which are formulated as research questions for this thesis.

The data used as well as known biases and correction procedures are covered in Chapter 4. The methodology of research and design of experiments conducted are given in Chapter 5. A substantial part of Chapter 5 is focused on nonparametric models advocated in this study as they play a central role in examining nonlinearities.

The results of this thesis are divided into three chapters. The objective of Chapter 6 is two-fold. Firstly, it establishes a nonparametric approach as a bona fide technique for modeling hedge funds' nonlinear risk exposures. Secondly, nonlinear risk exposures are examined in hedge fund style portfolios and details of in- and out-of-sample tests are presented. Chapter 7 continues the discussion of results as it reveals the findings on nonlinear risk exposures in individual funds. It also connects two streams of literature on nonlinearities and hedge fund performance, as it discusses the results pertaining to the performance of funds with and without nonlinear risk exposures. Chapter 8 contains the results on the linear and the nonlinear replication of hedge fund style benchmarks and investable indices. Finally, Chapter 9 summarizes the findings and provides concluding comments.

1.4 Software

R version 3.0.2 (R Core Team, 2014) was the main computational engine used in the thesis. Additional packages were downloaded from the Comprehensive R Archive Network (CRAN)[5]. R software was used to estimate all the models, perform the statistical analysis and prepare figures and tables with results. All tasks related to data processing were performed using Microsoft SQL Server 2008 and SQL Server Management Studio. The thesis was written using Microsoft Word 2010 and EndNote X7.

[5] http://cran.r-project.org/

Chapter 2 Hedge Funds' Background

This chapter outlines the main details about the institutional setting of the study as well as hedge funds' characteristics and regulatory environment.

2.1 Institutional Setting

Although hedge funds have been in existence for over half a century there is no common or legal definition of the term 'hedge fund'[6]. On the contrary, some of the existing definitions are contradictory[7]. The disagreement over a standard definition reflects the heterogeneity of hedge funds as an asset class on the one hand, and difficulty of gaining insights into the industry due to the lack of transparency of hedge funds on the other. Nevertheless, there are several important features shared by most of hedge funds which help to classify an investment vehicle as a hedge fund.

First of all, hedge funds set an absolute performance target, i.e. they seek to generate positive returns regardless of prevailing market conditions. Based on this premise hedge funds are traditionally considered to have low correlations with market variables and provide diversification potential for a traditional portfolio of equities and bonds.

Secondly, hedge funds are granted full flexibility to invest in any financial market and instrument. They have access to traditional financial markets including equities, bonds, currencies, and commodities; other markets including private equity and property; specific

[6] Technical Committee of the International Organisation of Securities Comissions, "The regulatory environment for hedge funds. A survey and comparison", 2006.

[7] See examples in (Lhabitant, 2006, p. 25)

markets niches such as distressed securities and leveraged loans; and derivative markets. Also they do not have restrictions on short selling and applying financial leverage.

Thirdly, hedge funds often impose impediments on capital inflows and withdrawal. For example, it is common for hedge funds to include statutory restrictions on the number of investors; set a high minimum investment amount; introduce lockup periods, redemption periods, advance notice periods, subscription periods; close funds for new investors[8]. Also, there can be implicit restrictions driven by illiquidity in the assets held by hedge funds.

Fourthly, hedge funds charge much higher fees than other traditional fund managers. The regular annual management fee varies from 1% to 2% of portfolio assets. In addition, hedge funds utilize a performance-based fee, which typically varies between 15% and 20% of new profits earned each year (Goetzmann, Ingersoll, & Ross, 2003). Incentive fee is paid only from the amount of net asset value (NAV), which exceeds high-water mark (the highest previous NAV). If the end-of-year NAV is below high-water mark, incentive fee is not collected and, most importantly, the fund manager is not penalized. Thus, hedge fund incentive contracts represent a call option to the manager on fund’s profits.

Finally, hedge funds are not bound by strict reporting requirements applicable to mutual funds and other collective investment schemes. They are usually set up as limited partnerships with investors named as limited partners and fund managers acting as general partners. Until recently hedge funds in the US were not obligated to register with the Securities and Exchange Commission (SEC). This situation however has started to change following the recent financial crisis, where regulators have initiated a major overhaul of the

[8] For a detailed discussion on share restriction in hedge funds, see Getmansky, Liang, Schwarz, and Wermers (2011)

financial system which has also impacted the hedge fund industry. The main outcome of the financial reform is the Dodd-Frank Wall Street Reform and Consumer Protection Act signed into US federal law on July 21, 2010. The law requires all large hedge fund advisors[9] to register with the SEC, maintain extensive records about their investment and business practices, and provide such information to the SEC, hire a chief compliance officer to design and monitor a compliance program and be subject to periodic SEC examinations and inspections. Hedge funds trading over-the-counter derivatives may also be designated as major market participants and thus be subject to additional regulation. The evaluation of the impact of this regulatory change on hedge funds is still too early to determine.

In summation, hedge funds differ from other investment vehicles in many ways. Their lighter regulatory environment enables hedge funds to pursue more complex trading strategies, but it is this associated complexity and lack of transparency, that makes understanding their activities difficult.

2.2 Hedge Fund Styles

Despite common attributes shared by most hedge funds, the hedge funds universe represents a very heterogeneous collection of investment vehicles. Hedge funds pursue a plethora of investment strategies and have different risk-return profiles. Bookstaber (2003) argues that the characteristics-based definition of a hedge fund, similar to one outlined in the previous section, encompasses all possible investment vehicles and all possible investment strategies, minus the small subset of "traditional" strategies. As a result, it is too wide to enable any meaningful analysis.

[9] A large fund is defined as one with AUM in excess of $150 million. Also, there are exemptions for family offices and venture capital fund advisors.

To address this concern, hedge funds are typically classified into groups known as hedge fund categories or styles. Styles are typically defined based on either the trading strategy (e.g. trend following style), geographical (e.g. emerging markets style) or asset class (e.g. long-short equity style) focus. So far unfortunately, there is no commonly accepted classification scheme for hedge fund styles; depending usually on the styles adopted by the data providers. Since hedge funds report voluntary to commercial databases, and the database providers generally do not verify the styles designated by the hedge funds, such a classification is described as being a 'self-reported' classification.

This thesis employs classification schemes developed by TASS and HFR[10]. The TASS database is one of the largest hedge fund databases. It is maintained by Credit Suisse. All funds in the TASS database are divided into 14 styles: Emerging Markets, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Fund of Funds, Global Macro, Long-Short Equity, Managed Futures, Multi-Strategy, Options Strategy, Other hedge funds, and Undefined hedge. The latter three categories are typically excluded from the analysis, leaving in total 11 categories. Description of TASS styles is provided in Appendix I.

In the HFR database, a widely used hedge fund database maintained by Hedge Fund Research (HFR), style classifications differ from those adopted by TASS. HFR classifies hedge funds into four broad categories, Equity Hedge, Event Driven, Macro and Relative Value, for which each also has a number of sub-categories. The HFR definitions are listed in Figure 2.1, and further descriptions of these categories, as well as a number of their sub-categories, are given in Appendix II.

[10] For more details on these databases, see Chapter 4

Figure 2.1 HFR Hedge Fund Strategy Classifications

Hedge Fund Strategy Classifications			
Equity Hedge	**Event Driven**	**Macro**	**Relative Value**
Equity Market Neutral	Activist	Active Trading	Fixed Income - Asset Backed
Fundamental Growth	Credit Arbitrage	Commodity: Agriculture	Fixed Income - Convertible Arbitrage
Fundamental Value	Distressed / Restructuring	Commodity: Energy	Fixed Income - Corporate
Quantitative Directional	Merger Arbitrage	Commodity: Metals	Fixed Income - Sovereign
Sector: Energy/Basic Materials	Private Issue/ Regulation D	Commodity: Multi	Volatility
Sector: Technology/Healthcare	Special Situations	Currency: Discretionary	Yield Alternatives: Energy Infrastructure
Short Bias	Multi-Strategy	Currency: Systematic	Yield Alternatives: Real Estate
Multi-Strategy		Discretionary Thematic	Multi-Strategy
		Systematic Diversified	
		Multi-Strategy	

Source: Hedge Fund Research

Due to the voluntary and 'self-reporting' nature of hedge fund disclosure, misclassification of funds may occur. The performance information contained within the commercial databases used is therefore likely to contain some forms of bias. These potential biases will be discussed later in Section 4.2.

Chapter 3 Literature Review

This chapter develops theoretical underpinnings of the thesis and reviews studies related to modeling and evaluation of hedge funds' nonlinear risk exposures. As set out in the introduction chapter there are three main research areas associated with the topic of this study:

- Modeling and assessment of nonlinearities in hedge fund style portfolios;
- Modeling and assessment of nonlinearities in individual hedge funds;
- Replication of hedge funds' linear and nonlinear systematic risk exposures and comparison of clones with investable and non-investable hedge fund benchmarks.

Firstly, the thesis focuses on developing the methodology for examination of nonlinearities and its application to portfolios of funds grouped by fund style. Secondly, the analysis of nonlinearities is extended to individual funds in order to investigate differences in risk exposures and performance between funds within styles. Thirdly, the robustness of findings about linear and nonlinear risk exposures is verified by testing linear and nonlinear hedge fund replication models.

Accordingly, the structure of this literature review is as follows. To start with Section 3.1.1 discusses some typical hedge fund trading strategies with the particular focus on potential nonlinear systematic risk exposures. The discussion of trading strategies is important as it helps to understand the economic rationale behind common nonlinear systematic risk patterns which will be demonstrated further in the result chapters. Section 3.1.2 lays down theoretical foundation of the study. It provides arguments as to why traditional asset pricing models might not work well for hedge funds. Sections 3.1.3-3.1.4 review existing methods to model nonlinear hedge funds' risk exposures and document asymmetric anomalies in risk exposures known from the literature. Sections 3.1.5-3.1.6 formulate the first and the second research questions pertaining to the first two areas of investigation.

Section 3.2 is devoted entirely to third area of investigation, i.e. replication of linear and nonlinear risk exposures. Section 3.2.1 explains the rationale and concept of hedge fund replication. Section 3.2.2 discusses the existing approaches and replication models, whilst Section 3.2.3 discusses the choice of replication benchmarks, i.e. non-investable broad indices vs. investable indices. Finally, Section 3.2.4 formulates the third research question.

3.1 Hedge Funds' Nonlinear Risk Exposures – Theory, Models and Empirical Evidence

3.1.1 Systematic Risk in Hedge Fund Strategies

Hedge fund strategies are often viewed as the antitheses of the passive investment approach. Considered as an enhancement of the traditional active management strategies, they provide potentially more opportunities to generate alpha or abnormal returns for investors. They have a wider arsenal of financial instruments available to them; and provide lucrative incentive contracts that attract the most talented managers into the industry.

Academic research during the last two decades has however challenged the traditional view of hedge funds as providers of alpha. After the first commercial hedge fund databases became available in late 1990s, research revealed that hedge fund managers extracted a significant part of their returns from systematic risk premium, or beta, rather than alpha (Amenc, El Bied, & Martellini, 2003; Capocci & Hubner, 2004; Fung & Hsieh, 1997a; Schneeweis, Kazemi, & Martin, 2002). Unlike common investment strategies employed by traditional funds (e.g. size and value investing) however, hedge fund strategies are typically more complicated and diverse, as they target more specific risk exposures in various market niches. Instead of a single source of systematic risk, as underlies the CAPM, hedge funds appear to have many sources of systematic risk, or multiple risk exposures to various aspects of systematic risk. These alternative sources of systematic risk, exploited by hedge funds, have been labelled as alternative beta strategies (Jaeger, 2008).

Although alternative beta strategies, discussed in more detail below, may seem exotic for traditional investors who are used to holding portfolios of equities and bonds, the fundamental finance principle of risk-return trade-off still remains valid for alternative beta. An investor taking exposure to any non-diversifiable risk requires compensation, usually in the form of a positive expected return. Examples of alternative risk premium are numerous, and include the financial distress risk premium earned when writing deep out of the money put options, or making bets on the successful consummation of a corporate merger/acquisition transaction; , or when earning a liquidity premium for holding illiquid securities, e.g. securities of companies undergoing restructuring[11].

Academic studies have further highlighted another significant difference between hedge funds and traditional funds. While mutual funds' strategies are often akin to a buy-and-hold strategy, hedge funds' strategies are very dynamic. As a result, instead of a linear pattern of exposures to systematic risk, as in buy-and-hold strategies, a hedge funds' risk exposure can

[11] For details and other examples, see Jaeger (2008)

have an asymmetric profile. In other words, the correlation between their returns and alternative betas can be nonlinear (Fung & Hsieh, 1997a, 2001). For instance, many equity-oriented and risk-arbitrage hedge fund strategies are found to have payoffs resembling a short put option position on the market index (Agarwal & Naik, 2004; Mitchell & Pulvino, 2001).

To better understand the nature of systematic risk in hedge funds, as well as these potential sources of nonlinearities, it is necessary to review the typical trading strategies in each of hedge fund categories. To this end, Table 3.1 contains a brief summary of the trading strategies employed by hedge funds. Common hedge funds categories are extracted from the TASS and HFR styles outlined in Section 2.2. The table lists hedge fund categories, typical trading strategies and dominant systematic risk exposures. The table does not provide an exhaustive list of all trading strategies, as there are myriad of them; rather it describes the most common strategies to gain a deeper insight into activities of hedge funds and facilitate further discussion of nonlinear risk. The rest of this section discusses each category in detail.

Equity Hedged

Equity oriented hedge funds predominantly focus on stock selection strategies using various investment approaches such as fundamental evaluation and top-down macro analysis. They may also have a specific regional, sector or other emphasis, where for example, a fund may focus on investing in the equity of companies from developing countries[12] or in perhaps those from the high tech sector. Besides stock picking, some equity managers attempt to pursue market timing strategies.

[12] Funds focusing on emerging markets sometimes are considered as the Emerging Markets style. The difference, however, is that the Emerging Markets category focuses not only on equities but on emerging markets debt as well.

The ideal payoff profile of an equity oriented fund resembles a call option when participating in a bull market, and a put option when seeking protection against losses in a bear market. Empirical studies find little evidence however to support this notion (Fung & Hsieh, 2004a). Equity oriented funds are found rather to exhibit directional net long or short exposures to the broad market or its sectors. They have also been found to participate in style investing, taking particular advantage of the spread between small cap and large cap stocks (Fung & Hsieh, 2004a).

Equity Market Neutral

While most of the equity oriented funds select stocks separately for the long and short sides of their portfolio, and thus often have a net long or short systematic exposure, equity market neutral funds aim to avoid directional bias. The total portfolio net exposure in terms of size, market beta, country, currency, industry or style (i.e. value and growth stocks) is supposedly controlled to be close to zero. Equity market neutral managers select stocks to take advantage of outperformance of the long positions relative to the short positions, with pairs trading being one of common market neutral strategies[13]. Pairs trading involves taking two opposite positions in closely related stocks, e.g. long and short position in stocks from the same sector with similar business models and balance sheets. If the prices of these two stocks diverge substantially, the strategy is to short the outperforming stock and buy the underperforming stock. The investment bet being that the spread between the stocks will eventually converge, aligning the two prices to their fair value, and so generating a profit for the investor. There are many types of market inefficiencies or anomalies documented,

[13] The strategy was pioneered by Gerry Bamberger and later led by Nunzio Tartaglia's quantitative group at Morgan Stanley in the 1980s (Gatev, Goetzmann, & Rouwenhorst, 2006)

which impact relative stock valuations over short periods, and which can be exploited profitably using equity market neutral strategies.

Although market neutral funds tend to have lower correlations with the market than do other styles, a situation consistent with their strategy proposition, they have been found to be not completely market neutral, exhibiting linear and nonlinear systematic exposure to market risk, as well as Fama and French's (1993) size and value factors. Patton (2009) tested equity market neutral funds for correlation neutrality, variance neutrality, value-at-risk neutrality, and tail neutrality, and found that at least one-quarter of these funds were not completely market neutral.

Fixed Income Arbitrage

Fixed income arbitrage managers, as their name suggests, trade fixed income securities in the liquid government, municipal, corporate and securitized bond markets, whereby they try to exploit second- and third-order effects, such as curvature, volatility and mispricing of global yield curves. These funds generally seek profits by trading the spread relationship between related fixed income securities and their derivatives. The three major investment styles in fixed income arbitrage strategies are directional trading, relative value and market neutral (Lhabitant, 2006). Directional strategies, such as yield curve spread trading take directional bets on the future interest rates, spreads and the shape of yield curve. Relative value strategies seek to take advantage of relative pricing anomalies between several fixed income securities whilst maintaining a diversified risk profile. Market neutral fixed income strategies are similar to relative value strategies, but they systematically hedge their exposure to interest rate variations. For instance, some funds engage in trading the yield spread between recently issued government bonds ('on-the-run' bonds) and the second most recent issue ('off-the-run' bonds). On-the-run issue typically trades at lower yield due to higher liquidity comparing with the off-the-run issue. Thus, if the basis (difference in price) between an on-the-run and off-the-run instrument becomes large, a fund manager may buy the off-the-run and sell the on-the-run bond in anticipation of the basis shrinking.

Fixed income arbitrage funds are often considered as providers of economic disaster insurance. Essentially they take positions that correspond to short put positions on financial market turmoil, exposing themselves to sudden event risk (Jaeger, 2008, p. 50). That is why investment professionals refer to the Fixed Income Arbitrage style as "picking up nickels in front of a steamroller"; fixed income arbitrage funds provide relatively small returns most of the time, but also have the potential to incur large losses. Empirical analysis of fixed income arbitrage strategies confirms that most of them are sensitive to various equity and bond market factors. For example, the swap spread arbitrage strategy is sensitive to problems in the banking sector; the mortgage arbitrage strategy is sensitive to a large drop in interest rates, triggering a rise in prepayments; the yield curve arbitrage strategy has returns that are related to the combinations of Treasury returns that mimic a ''curvature factor''; and the capital structure arbitrage strategy has returns that are related to factors that proxy for economy-wide financial distress[14] (Duarte, Longstaff, & Yu, 2007, p. 802).

Convertible Arbitrage

The convertible Arbitrage category consists of funds which trade convertible securities, such as convertible bonds, convertible preferred stock and warrants. A typical convertible arbitrage strategy starts with a bottom-up valuation analysis that seeks to identify potentially undervalued convertible securities. This is a non-trivial task, as the pricing of

[14] For explanation of these strategies, see Table 3.1

convertible securities is complex and subject to substantial model risk. As there is currently no universal valuation model for convertibles, the manager must first develop an 'in-house', proprietary model. Within this valuation model, the price of a convertible security may depend on many different factors. For example, factors that may influence the convertibles value include interest rates and credit quality, the premium over the conversion values, stock prices and stock price volatilities, call and put schedules associated with the bond, liquidity, open short interest of the stock, and so on. Once a set of 'cheap' securities have been identified, the manager buys the securities, usually using financial leverage. Applying leverage allows the manager to amplify profit margins and provide more liquidity to convertible bond issuers[15]. Since convertible securities are directly exposed to equity, interest rate and credit risks[16] a manager may hedge these risks (or at least some of them) by targeting a market neutral position. Alternatively, the manager can take a fundamental view of the assets, and build their assessment into a net long (in terms of equity/interest rate/credit risk exposure) or short position. Accordingly, returns of the convertible arbitrage strategy are affected by systematic exposure to equity, volatility, interest rate and credit risks. Also, convertible arbitrage funds may be adversely affected by liquidity risk and liquidity shocks in the market, since they rely on borrowing short-term capital from brokers and raise long-term capital from investors. Empirical evaluation of convertible arbitrage funds conducted by Agarwal, Fung, Loon, and Naik (2011) shows that a significant proportion of the variation of convertible funds' returns is explained by a combination of a

[15] Anecdotal evidence suggests that some convertible arbitrage hedge funds employ a leverage ratio of up to $5 borrowing to $1 equity (Zuckerman, 2008).

[16] See Chan and Chen (2007), Das and Sundaram (2004), and Davis and Lischka (1999), among others, for discussion on the impact of market, credit and interest rate risks on convertible bond pricing.

buy-and-hold and buy-and-hedge strategies[17]. In general Agarwal, Fung, et al. (2011) posit that a typical convertible arbitrage hedge fund manager assumes the role of an intermediary – providing financing to the convertible securities issuers, while distributing part of the equity risk of convertibles ownership to the equity market through delta hedging.

Event Driven

Event driven funds seek to exploit pricing inefficiencies that may occur before or after corporate events, such as, bankruptcy, merger, acquisition, spinoff, litigation, stock inclusion or exclusion from stock index etc.[18] The event driven funds sector was originally dominated by merger arbitrage related strategies, but has now expanded to cover a larger selection of corporate events. In the case of a merger transaction, when a company signals its intent to buy another company, the stock price of the target company typically rises, whilst the stock price of the acquiring company typically declines. The stock price of the target company however usually remains below the acquisition price. It is considered that this discount is due to the market's uncertainty about success of the merger deal. A merger arbitrageur can then buy the stock of the acquisition target and, if not a cash merger, simultaneously short the bidding company's stock. The arbitrageur makes a profit if and when the acquisition goes through. This strategy is not a pure arbitrage, but rather a speculation on an event occurring. Since the probability of a successful deal consummation varies in different market states, merger arbitrage funds' have exposure to market risk, which has a nonlinear form. The returns are positively correlated with market returns in severely depreciating markets,

[17] In Agarwal, Fung, et al. (2011) buy-and-hold convertible bond strategy is proxied by returns of Vanguard Convertible Securities mutual fund; the return on the buy-and-hedge strategy equals that on a long position in newly issued convertible bonds and that on a short position in the corresponding stocks.

[18] http://www.barclayhedge.com/research/educational-articles/hedge-fund-strategy-definition/hedge-fund-strategy-event-driven.html

but uncorrelated with market returns in flat and appreciating markets (Mitchell & Pulvino, 2001). Returns therefore to merger arbitrage are similar to those obtained from selling uncovered index put options.

Another sub-category within the Event Driven style is known as Distressed Securities. Distressed securities strategies invest in (or less frequently sell short) debt, equity or trade claims of companies in financial distress or already in default. The securities of companies in distressed or near default situations typically trade at substantial discounts to par value. The discount reflects difficulties in analysing and accurately valuing securities during restructuring proceedings. The 'Active' distressed securities fund managers may participate in creditor committees, and assist with recovery or reorganization processes. 'Passive' fund managers will buy and hold distressed securities until they appreciate to desired level or focus on short-term trading in the anticipation of specific events, such as the outcome of a court ruling or important negotiations. Jaeger (2008, p. 69) has posited that at least part of the returns of distressed securities managers are related to systematic risk premia. The author proposes that in environments of falling equity markets, rising interest rates, and widening credit spreads, the performance of distressed securities investment is highly correlated to the broader market. For example, the distressed securities strategy underperformed other hedge fund strategies during 2000-2002, when conditions in the credit markets deteriorated, while it showed strong performance in the period 2004-2007 when credit spreads narrowed significantly.

Global Macro

Global Macro managers carry long and short positions in any of the world's major capital or derivative markets. Global macro investing is based on the manager's anticipation of price movements in the global capital markets. Managers of these funds employ fundamental analysis of micro- and macroeconomic indicators and/or technical indicators, such as trends and patterns in recent prices. An example of a global macro strategy is currency carry trading. Currency carry trading involves investment in high-yield currencies financed by borrowing in a low-yield currency. The strategy assumes risk exposure to unexpected exchange rate movements.

The Global Macro category combines highly heterogeneous and opaque spectrum of funds, which might have very different sets of systematic risk exposures. Overall, due to directional bias to global markets, global macro funds are typically exposed to a wide set of common risk factors, including market risk, foreign exchange risk, interest rate risk, commodity risk, size and value spreads etc.

Managed Futures

Managed Futures or Commodity Trading Advisors (CTAs) seek returns through taking long and short positions in highly liquid, regulated, exchange-traded instruments such as futures and options on stocks, foreign exchange, commodities and fixed income. Within the CTA category, there are two groups of managers using two different investment approaches – designated as either systematic or discretionary funds (some managers may also use a combination of both). Systematic CTA strategies are mechanistic and driven by pre-specified trading algorithms. Buy and sell orders are generated by computer models that combine various technical factors and indicators. The trend following strategy is the dominant trading style within the Systematic Managed Futures sub-category (Billingsley & Chance, 1996). Trend traders attempt to capture gains through the analysis of an asset's momentum in a particular direction. They enter into a long position when a stock is trending upward; and a short position when the stock is in a downward trend. As will be explained in more detail later (see, Section 3.1.3.1), returns of trend following funds exhibit option-like features – they tend to be large and positive during the best and worst performing months of the world equity markets (Fung & Hsieh, 1997b).

Discretionary CTAs mostly rely on a manager’s judgment, and their evaluation of the fundamentals and market indicators in making investment decisions. Discretionary CTA strategies include: top-down macro, fundamental analysis and market-neutral strategies. They also exploit temporary mispricing situations through faster and better access to information. For instance, discretionary CTA managers may have knowledge about the inventory levels of commodity producers and can interpret new information accordingly. Similar to global macro managers, discretionary CTAs employ a diverse range of strategies and have broad exposures to a variety of systematic risk factors.

In conclusion, systematic risk is present in most of the hedge fund strategies. Due to various reasons including dynamic nature of trading strategies, usage of derivatives and short selling hedge funds’ exposures to market proxies of risk may take a nonlinear form, such as in the case of exposures of relative value strategies (e.g. event driven, fixed income arbitrage) to stock market returns in different market conditions. Therefore, it is important to examine nonlinear risk exposures of hedge funds in order to provide an empirical evidence of systematic risk in hedge funds.

Table 3.1 Hedge Fund Strategies and Dominant Systematic Risk Exposures

Hedge Fund Category	Common Trading Strategy	Description	Dominant Systematic Risk Exposure
Equity Oriented	Fundamental Analysis	Stock selection based on stocks' fundamentals and financial statements analysis	• Market Risk • Size Spread • Volatility Risk
	Top-Down Analysis	Stock selection based on macro analysis of the global economy and financial markets and then breaking these components down into finer details up to the industry and company level	
	Equity Hedged	Buying a core set of stocks and partially hedging long position with short sales of other stocks. Examples include longing undervalued countries/sectors/stocks and shorting overvalued countries/sectors/stocks	
	Market Timing	Strategy of buying or selling stocks (or other financial assets) based on predictions of future market price movements	
	130-30 (100X-X)	Strategy of short-selling 30% (XX) of portfolio by selling poor performing stocks and leveraging by an equal amount long positions and purchasing 130% ((100+X)%) shares that are expected to have high returns	
	Shareholder Activism	An activist hedge fund starts with a purchase of shares it considers undervalued and then uses an equity stake in a corporation to put public pressure on its management to adopt certain changes in order fix the issues and improve share performance	
Equity Market Neutral	Pairs Trading	Strategy involves two closely related stocks, e.g. similar stocks of the same sector. It shorts the outperforming stock and goes long the underperforming one. The bet is that the "spread" between the two prices will eventually converge.	• Market Risk • Size Spread • Value Spread
	Market Inefficiencies Arbitrage	Detecting and exploiting short-term market anomalies and inefficiencies as the difference between market price and a theoretical 'fair value' price determined by a valuation model	
Fixed Income Arbitrage	Yield Curve Spread Trading	Taking opposing positions in two maturities on the yield curve in anticipation of a steeper/flatter yield curve	• Interest Rate Risk o Government Bonds o Corporate Bonds o Convertible Bonds o Municipal Bonds o MBS/ABS • Credit Risk • Market Risk • Volatility Risk • Liquidity Risk
	Yield Curve Arbitrage	Similar to a butterfly option strategy; involves taking long and short positions at different points along the yield curve. Small parallel moves in the yield curve would have little effect on the strategy payoff; however, large parallel moves in either direction will guarantee a positive return.	
	Swap Spread Arbitrage	Taking opposing long and short positions in a swap and a Treasury bond; swap spread is a form of "credit spread" insofar as it represents a direct comparison between the private credit risks represented in interest rate swap markets vs. public credit risks represented in Treasury markets	
	Capital Structure Arbitrage	Strategy that seeks to profit from the pricing differentials between various claims on a company, such as its debt and stock with the expectation that the pricing disparity between the two securities will cancel out	
	Credit Spread Arbitrage	Capturing yield curve differentials for securities with different credit qualities	
	Mortgage Arbitrage	Strategy of buying pass-through mortgage-backed securities (MBS) and hedging their interest rate exposure with swaps; the main risk of a MBS pass-through is prepayment risk, i.e. the risk of homeowners exercising their option to prepay their mortgages.	
	Volatility Arbitrage	Strategy is often implemented by selling options and simultaneously delta-hedging the exposure to the underlying asset; the bet is that implied option volatility will exceed subsequent realized volatility.	
Convertible Arbitrage	Buy-and-Hedge	Strategy involves buying undervalued convertible bonds and hedging the equity exposure by selling short underlying stock/stock option/index futures/index options	• Market Risk • Credit Risk • Interest Rate Risk • Liquidity Risk • Volatility Risk
	Buy-and-Hold	Strategy involves buying undervalued convertible bonds as determined by trader's valuation model and holding them until maturity or selling prior to maturity in the market	
Event Driven	Merger Arbitrage	There are two types of this strategy depending of the type of the corporate merger: o Stock-for-stock merger – the strategy involves buying the stock of the acquisition target and at the same time shorting the bidding company's stock. When the acquisition goes through the merger	• Market Risk • Credit Risk

		arbitrageur uses the converted stock to cover the short position; o Cash merger – the strategy involves buying the stock of the target company before the acquisition, and then making a profit if and when the acquisition goes through. In both cases the speculation is on an event occurring,	• Interest Rate • Volatility Risk
	Distressed Securities	Investing in (or less frequently selling short) debt, equity or trade claims of companies in financial distress or already in default. The securities of companies in distressed or defaulted situations typically trade at substantial discounts to par value due to difficulties in analysing and accurately valuing their securities. 'Active' managers may participate in creditor committees and assist recovery or reorganization process; 'passive' managers buy and hold distressed securities until they appreciate to desired level or focus on short-term trading in anticipation of specific events, such as the outcome of a court ruling or important negotiations.	
	Regulation D	Strategy involves investing in publicly listed companies, mostly of micro and small capitalization, in need of capital through privately negotiated structures, e.g. private equity placements pursuant to Regulation D of the US SEC Act of 1933.	
Global Macro	Tactical Trading	A broad range of investment strategies with a variable exposure to the broad liquid asset classes, including equities, bonds, currencies, commodities and derivatives. These strategies employ fundamental analysis or technical indicators and reflect managers' views on overall market direction as influenced by major economic trends and or events.	• Market Risk • Foreign Exchange Risk • Commodity Risk • Interest Rate Risk
	Currency Carry Trading	Strategy of investing in high-yield currencies financed by borrowing in a low-yield currency. It assumes risk exposure to unexpected exchange rate movements.	
Managed Futures/CTA	Trend Following	Strategy attempts to capture gains through the analysis of an asset's momentum in a particular direction. The trend trader enters into a long position when a stock is trending upward; and a short position is taken when the stock is in a down trend.	• Market Risk • Foreign Exchange Risk • Commodity Risk • Interest Rate Risk

3.1.2 Asset Pricing Theories and Hedge Funds' Nonlinear Risk Exposures

The previous section outlines typical strategies employed by hedge funds. It reveals that despite the apparent complexity of the strategies and structure of payoffs, hedge funds are nevertheless affected by systematic risk factors; albeit perhaps with risk exposures that have a nonlinear form. Accordingly, hedge fund pricing models should account for potential nonlinear effects. Unfortunately, the traditional asset pricing literature does not offer much help to address the issue. This is because theoretical assumptions underlying standard asset pricing theories are not well suited to hedge funds. This section clarifies this point in detail and explains why standard asset pricing theories fail if applied to hedge funds.

The first and the most well-known asset pricing theory is the Capital Asset Pricing Model (CAPM) (Lintner, 1965; Mossin, 1966; Sharpe, 1964; Treynor, 1961, 1962). It states that at equilibrium the expected excess return from holding an asset should be proportional to the covariance of its return with the market portfolio. In theory, the market portfolio is a value-weighted portfolio of all risky assets available in the economy, including financial assets, real assets and human capital. Under certain assumptions[19] the CAPM postulates a linear relation between expected return and systematic risk. The key assumption in the model is normality of a return distribution or, equivalently, as shown in Cochrane (2005, pp. 145-152), a quadratic form for the investor's utility function. When return distribution is normal, the knowledge of its first two moments, mean and variance, is sufficient for investors to make

[19] The full list of assumption can be found, for example, in Elton, Gruber, Brown, Goetzmann (2009, pp. 282-283)

investment decision, and therefore the relationship between the risk and return ought to be linear (Cochrane, 2005, pp. 145-152).

How plausible is the assumption of normality in the context of hedge funds[20]? As documented in prior studies, return distributions of most of the hedge fund strategies have been found to deviate severely from normality. Specifically hedge funds' return distributions have a fatter left tail and exhibit excess kurtosis and negative skewness (Lo, 2001; Malkiel & Saha, 2005). The descriptive statistics of hedge fund style returns presented in Section 6.1, confirms this fact. From a theoretical perspective, this deviation from normality is not surprising. There are at least several reasons to expect return distributions to be non-normal.

Firstly, peculiar distribution patterns may originate from the use of specific trading strategies (see, Table 3.1). As discussed in the previous section, hedge funds often pursue dynamic hedging and arbitrage strategies that result in payoff profiles and return distributions that are very different from the payoffs of the traditional asset management funds. As shown by Merton (1981), a market timing strategy that can be used to generate alpha, creates an asymmetric payoff pattern that implies a non-normal distribution of returns.

Secondly, hedge funds trade derivatives and other securities that have nonlinear payoffs. Derivatives are used by hedge funds to alter their risk-return characteristics, manage risk and enhance yields. An example of a common strategy which involves derivatives is a

[20] Since normal distribution assumption is equivalent to the assumption of quadratic utility function the discussion is focused on the distributional assumption only. The only comment regarding a quadratic utility function is that it implies increasing absolute risk aversion for increasing wealth, and that is not consistent with experimental and empirical evidence of mostly decreasing absolute risk aversion of investors (Friend & Blume, 1975).

protective put strategy. Hedge funds often act as providers of financial insurance by selling put options. In a normal market environment, deep out-of-the-money short put option positions generate small positive yields, due to the option premium; however, during extreme adverse market states the strategy leads to significant losses. If such derivatives strategies are not accounted for in the asset pricing model they may produce spurious positive alpha[21]. The protective put strategy however involves a few proprietary elements, does not require any specific skill, and essentially represents a bet on rare but possible events. Hence, it provides an example of an alternative beta strategy, rather than an alpha generating strategy. The distribution of returns from this strategy will also be negatively skewed with a heavier left tail than that of the normal distribution assumed by the CAPM.

The third reason for non-normal returns and nonlinear risk-return profiles is related to the asymmetric structure of incentive contracts. As discussed in Section 2.1 the incentive fee for a hedge fund manager can only be positive, because fund managers participate in sharing profits but are not penalized for losses. Such an asymmetric payoff of the incentive contract may be viewed as a free call option on the percentage of a fund's performance that is granted by the investor to the fund manager (Anson, 2001). The option has an exercise price of zero, a maturity of one year (usually) and volatility equal to the volatility of the hedge fund's before-fee returns (Lhabitant, 2004, p. 202). This incentive option encourages the manager to actively manage a fund's volatility and risk exposures. If the fund is a long-way below the high-water mark, it is tempting for the manager to increase the level of risky bets, in the hope of a quick recovery[22]. In contrast, if the fund is a long-way above the high-water

[21] For a detailed explanation of the protective put strategy and a numerical example in the hedge fund context, see Hasanhodzic and Lo (2007, pp. 8-10)

[22] In the extreme scenario a fund manager may even close the fund and start up a new one, with a new high-water mark (Kahn, Scanlan, & Siegel, 2006)

mark, the manager may try to reduce risk exposures and minimize the fund's volatility (Kahn et al., 2006). This asymmetric structure of incentive fees may facilitate option-like patterns in hedge fund returns and induce non-normal patterns in return distributions (Brooks, Clare, & Motson, 2007).

Finally, other characteristics of hedge funds may exacerbate non-normal anomalies and generally are not aligned with the assumptions of the CAPM. These features include the flexibility in applying financial leverage, trading illiquid securities, imposing restrictions on capital flows, and information asymmetry between fund manager and investor due to lack of binding disclosure requirements (see Section 2.1).

Due to these hedge fund features, which violate the CAPM, it is not surprising that empirical tests with regards to hedge fund returns demonstrate that the model is unsatisfactory. Lhabitant (2004) finds that the CAPM explains less than 30% of the return variation for funds outside the equity oriented categories. Also, as a result of model misspecification, hedge funds are found to have large positive and significant alpha. This large alpha is reduced drastically however once some of the alternative beta exposures are taken into account (Capocci & Hubner, 2004).

Another conventional asset pricing model is the Arbitrage Pricing Theory model (Ross, 1976). One of the principal implications of the CAPM is that the stochastic discount factor (SDF) used to price all assets is a linear function of a single factor, the portfolio of aggregate wealth. Since the inception of the CAPM, numerous studies have documented violations of this postulate[23]. The aggregate wealth variable, which in theory comprises all assets in the

[23] The literature on the APT is ample. References may be found, for example, in Campbell, Lo and MacKinlay (1997).

market, is not directly observable. Thus, in practice for the sake of simplicity it has been traditionally substituted with market proxies, which account only for equity risk. The APT, in contrast to the CAPM, explicitly ascertains that several state variables or factor portfolios may be needed to explain expected returns. The value of an uncertain future payoff comes as compensation for taking risks related to these factor portfolios. Unlike with the CAPM however, the APT does not itself reveal the identity of priced factors. Thus, investors have to identify the appropriate set of risk factors to obtain correct prices.

Although the APT permits multiple risk factors and lays down the foundation for multi-beta or multi-factor models (Sharpe, 1992), it still retains the linear functional form adopted in the CAPM. The unconditional version of the APT model assumes that payoffs are linear in the factors and in idiosyncratic noise, which leads to an approximate linear relationship between the unconditional mean return and factor loadings.

Similar to the distributional assumptions underlying the CAPM, the question that arises with regards to the APT model is as follows: to what extent is the linear assumption applicable for hedge funds?

A number of asset pricing studies have investigated implications of the linear assumption in the APT model from a theoretical perspective. Dybvig and Ingersoll (1982) point out that linear beta pricing models assign negative prices to some states of nature and may price option contracts incorrectly, even when they assign correct value to underlying assets. Bansal and Viswanathan (1993) generalize the idea and argue that any derivative security with a nonlinear payoff function cannot be priced by the linear APT model. This motivates the authors to construct a pricing kernel without imposing a linear structure. Bansal and Viswanathan's (1993) pricing model makes only two general assumptions about the pricing kernel: low dimensionality (i.e. the kernel depends only on a few economy-wide factors) and non-negativity (no arbitrage requirement). The model they develop has no restrictions with regards to functional form of the pricing kernel and can be used to price any security. However, functional flexibility of the model comes at a cost of estimation complexity - the model is estimated nonparametrically.

Several studies have tested asset pricing models with nonlinear pricing kernels and confirmed their superior performance relative to linear models. For example, Dittmar (2002) finds empirical evidence that the model with a nonlinear pricing kernel performs better than a standard linear model for portfolios of equity securities. Aït - Sahalia and Lo (1998) demonstrate that a nonparametrically estimated state-price density has a better forecasting ability for prices of call and put options comparing with the Black-Scholes (1973) model assuming normal return distribution.

In the context of hedge funds, as explained above, it is reasonable to expect payoffs to be nonlinear functions of payoffs of the underlying assets in the portfolio. Same reasons which cause return distributions to be non-normal may lead to nonlinear relationship between a hedge funds' expected returns and systematic risk factors.

Summarizing all arguments regarding the assumptions underlying the CAPM and the APT, it is concluded that a linear form of the relationship between expected return and risk may not hold for hedge funds. Hence, an examination of the nonlinear structure of hedge fund payoffs is warranted and should help gain a better understanding of the return generating process of hedge funds.

3.1.3 Modeling Nonlinear Hedge Fund Risk

In the previous section, we discussed the key theoretical assumptions underlying the standard asset pricing models, and explained why those models are not suitable for hedge funds. This issue has been recognized in the literature and some efforts have been made to explore nonlinear patterns in hedge fund strategies. Accordingly, this section reviews three models of hedge fund returns and discusses their advantages and drawbacks and documents empirical evidence of nonlinearities in hedge fund categories. Table 3.2 contains a summary of the known nonlinear anomalies as identified from the literature.

Table 3.2 Empirical Evidence on Hedge Funds' Nonlinear Risk

Reference	Data Sample	Hedge Fund Category	Risk Factor	Pattern of Risk Exposure
Fung and Hsieh (1997a)	Paradigm LDC; TASS, 1991-1995;	Systems/Trend following	US equity	Straddle
		Systems/Trend following	Non-US equity, non-US bond, US dollar	Asymmetric
		Systems/Opportunistic	Gold	Call option
		Systems/Opportunistic	US bonds, non-US bonds, US dollar	Asymmetric
		Global/Macro	US dollar	Straddle
		Global/Macro	Gold, emerging markets equity	Asymmetric
		Distressed	High yield corporate bonds	Asymmetric
Fung and Hsieh (1997b)	TASS, 1986-1996	Commodity Trading Advisors	World equity	Straddle
Fung and Hsieh (2001)	TASS, 1986-1998	Trend Following	World equity	Straddle
			PTFSBD, PTFSFX, PTFSCOM[24]	Linear
Mitchell and Pulvino (2001)	CRSP, 1963-1998	Hypothetical Risk Arbitrage Index Manager	Equity	Short put option
Agarwal and Naik (2004)	HFR, 1990-2001; TASS, 1994-2001	HFR Event Arbitrage	US equity	Short out-of-the-money put option
		HFR Restructuring	US equity (S&P 500)	Short out-of-the-money put option
		HFR, TASS Event Driven	US equity (S&P 500)	Short out-of-the-money put option
		HFR Relative Value Arbitrage	US equity (S&P 500)	Short out-of-the-money put option
		HFR Convertible Arbitrage	US equity (S&P 500)	Short at-the-money put option
		HFR Short Selling	US equity (Russell 3000)	Short out-of-the-money call option
Fung and Hsieh (2004b)	HFR, MSCI, TASS,	TASS Hedge Fund Composite	PTFSBD, PTFSCOM	Linear
		TASS equal-weighted portfolio of all funds	PTFSFX, PTFSCOM	Linear
		MSCI Hedge Fund Composite	PTFSFX	Linear
Chen (2007)	HFR, TASS equal-weighted indices[25], 1994-2002	Convertible Arbitrage	High yield bonds	Convex
		Fixed Income Arbitrage	High yield bonds	Convex
		Event Driven	High yield bonds	Concave
		Emerging Markets	Emerging markets equity	Concave
		Global Macro	US government bonds	Concave
Chen and Liang (2007)	CISDM, HFR, TASS, 1994-2005	Equal-weighted portfolio of market timing funds[26]	US equity	Convex
Patton (2009)	HFR, TASS, 1993-2003	Equity Market Neutral	US equity	Nonlinear
Diez De Los Rios and Garcia (2011)	TASS, 1996-2004, equal-weighted	Event Driven	US equity	Not reported

[24] PTFSBD, PTFSFX and PTFSCOM are primitive trend following strategies (PRTFS) on bonds, currencies and commodities with payoffs mimicking payoffs of lookback straddles. The payoff of a lookback straddle is a nonlinear function of the price of the underlying asset and equals $\max(S_T - S_{min}, 0)$. Lookback options are not traded in the market and PTFS are constructed by rolling a pair of standard straddles. Since payoffs of PTFS are nonlinear functions, a linear exposure to PTFS can be interpreted as a nonlinear exposure to PTFS' underlying asset.

[25] Chen and Liang (2007) construct equal-weighted indices manually using funds from the TASS database. Original indices in the TASS database are value-weighted.

[26] Chen and Liang (2007) select funds from the 'Market Timing' style of CISDM and HFR databases and search manually for market timing funds across all the styles in the TASS database

	indices[27]	Managed Futures	US equity	Straddle
		Fixed Income	US equity	Short straddle
		Convertible Arbitrage	US equity	Short put option
Giannikis and Vrontos (2011)	HFR, 1990-2009	HFR Equity Hedge	Book-to-market factor (HML)	Convex, threshold at 25th quantile
		HFR Macro	World equity excluding US	Convex, threshold at median
			World government and corporate bonds	Positive, convex threshold at 75th quantile
			US dollar	Convex, threshold at median
			US equity volatility	Concave, threshold at 25th quantile
		HFR Relative Value	World equity excluding US	Convex, threshold at 25th quantile
			Commodities	Concave, threshold at 25th quantile
			US equity volatility	Concave, threshold at median
		HFR Event Driven	US equity volatility	Concave, threshold at -0.02
		HFR Merger Arbitrage	Emerging markets equity	Concave, threshold at 0.008
		HFR Equity market neutral	Book-to-market factor (HML)	Convex, threshold at 25th quantile
		HFR Fixed Income Corporate	Commodities	Concave, threshold at 75th quantile
			US equity volatility	Concave, threshold at 0.0013
			Last month return	Positive, complex, thresholds at -0.004 and 0.0013
		HFR Short Bias	US equity	Negative, convex, threshold at 25th quantile
		HFR Emerging Markets	World equity excluding US	Convex, threshold at median
			Size factor (SMB)	Convex, threshold at median
			US equity volatility	Concave, threshold at median
			Last month return	Positive, concave, threshold at median
		HFR Fixed Income Convertible Arbitrage	Carhart's momentum factor	Convex, threshold at -0.01
			High yield bonds	Positive, concave, threshold at -0.002
			US equity volatility	Concave, threshold at -0.0013
		HFR Distressed/Restructuring	Last month return	Positive, concave, threshold at 0.0075
		HFR Quantitative Directional	US equity	Positive, convex, threshold at -0.023
			Book-to-market factor (HML)	Convex and then concave, thresholds at -0.017, 0.0004
			US dollar	Convex, threshold at 0.006
Lahiri, Shawky and Zhao (2013)	TASS, last 20 years	Hedge funds in aggregate	US equity	Convex
			PTFSBD	Concave
			PTFSCOM	Concave
			PTFSTK	Concave
			Last month return	Convex then concave

[27] Diez De Los Rios and Garcia (2011) construct equal-weighted indices manually using funds from the TASS database. Original indices in TASS database are value-weighted.

3.1.3.1 The Seven-Factor Fung and Hsieh (2004) Model

Fung and Hsieh have produced a number of studies which have resulted in a model known in the literature as the seven-factor Fung and Hsieh (2004b) model. This section provides a brief overview of these studies and describes the model.

Fung and Hsieh (1997a) is the first study to highlight the importance of accounting for nonlinear risk in hedge fund research. Contrary to the traditional view of market neutrality for hedge funds, the study reveals that hedge funds have significant exposure to systematic risk. This exposure to systematic risk factors however is not simply linear, as in the mutual funds industry (Sharpe, 1992), but has a more complex form. Four out of five hedge fund styles (which are identified using a principal component analysis) exhibit nonlinear correlations with the market factors. This correlation does not remain constant, but instead varies across market states. For instance, the returns from the distressed style depends on the performance of high yield corporate bonds, but the trading strategy of distressed funds cannot be considered as a buy-and-hold strategy, because their returns during extreme market states are not in line with those in normal states. For the same reason, the Global/Macro style does not use buy-and-hold strategies in the U.S. bonds, world currencies, or emerging market equities, though the style is clearly exposed to price fluctuations in these markets. Further, the Systems/Opportunistic style is most profitable during rallies in the U.S. bonds, non-U.S. bonds, and gold markets, and during declines of the U.S. dollar. The Systems/Trend Following style is most profitable during rallies in non-U.S. equities and bonds, and during declines of the U.S. dollar. The only category with the trading strategy akin to a buy-and-hold strategy in the U.S. equity market is the Value style. It maintains a relatively constant correlation with the risk factor at different market states. Based on these results the authors conclude that hedge fund managers typically employ dynamic trading strategies that generate option-like payoffs with apparently no linear exposure to systematic risk.

In their subsequent work, Fung and Hsieh (1997b, 2001) focus on the trend-following funds. The trend-following strategy is the dominant strategy of one of the largest hedge fund styles, the Managed Futures or Commodity Trading Advisors (CTAs) (Billingsley & Chance, 1996). This strategy primarily relies on quantitative techniques to determine trends in the market and to generate trade signals. The authors argue that theoretically, a payoff of a fund that is able to perfectly predict price trends resembles a payoff of a *lookback straddle*[28]. They call the optimal trend-following strategy of buying lookback straddles as a Primitive Trend-Following Strategy (PTFS). The payoff of a PTFS is the following:

$$PTFS = S_{max} - S_{min} \quad \textbf{(3.1)}$$

where S_{max} and S_{min} are the maximum and minimum asset prices over a given time period. Since lookback options are not exchange-traded contracts, the authors reconstruct PTFSs by rolling a pair of standard straddles with the underlying asset in 26 different markets including world equities, bonds, commodities and currencies. After that the returns of the trend-following funds are modelled with PTFS portfolios. The authors find that the returns of trend-following funds during extreme market moves can be explained by a combination of PTFSs on bonds (PTFSBD), currencies (PTFSFX) and commodities (PTFSCOM). The average R^2 of a linear regression of the returns of 163 trend-following funds, on the returns of five

[28] A lookback straddle is a combination of long positions in a lookback call and put options. A lookback call/put option is a contract which grants the owner the right to purchase/sell an asset at its minimum/maximum price over a specified time period. A lookback straddle pays the owner the difference between the minimum and maximum price over a given time period, which is the same as a payoff of an “ideal” trend-following fund buying at the lowest price and selling at the highest price.

PTFS portfolios (stocks, bonds, three-month interest rates, currencies and commodities), is reported to be 24%, whilst the average R^2 for five buy-and-hold portfolios instead of the PTFSs is 11%. Higher explanatory power of the model with option-based factors suggest that trend-following funds have nonlinear exposures to systematic risk, which cannot be observed in the context of a linear-factor model applied to standard asset benchmarks.

Developing the idea of PTFSs further, Fung and Hsieh (2004b) combine three PTFS factors with four conventional asset-based style (ABS) factors and propose a hedge fund pricing model which is widely known in the literature as the seven-factor Fung and Hsieh (2004b) model (thereafter, the FH7 model)[29]. When applied to the fund of funds index the FH7 model explains 55% of return variability during 1994-2002 period. Out of three nonlinear factors only two (PTFSBD and PTFSCOM) appear to be significant.

Interestingly, while PTFS factors were originally proposed to capture option-like payoffs of trend-following strategies, since the work of Fung and Hsieh (2004b), the FH7 model has been routinely applied in the literature to model returns of all hedge fund styles, becoming a de-facto standard hedge fund pricing model. For example, most of the recent studies which estimate hedge fund alpha rely on the FH7 model (see, among others, Naik, Ramadorai, and Stromqvist (2007), Li, Zhang, and Zhao (2011), Titman and Tiu (2011), Patton and Ramadorai (2013) and Slavutskaya (2013)). Reliance on the ability of the FH7 model to capture a hedge funds' nonlinear risk exposures is even more surprising given that it has not been thoroughly tested. Fung and Hsieh (2004b, p. 78) note that "a standard way to gauge the usefulness of a model is to apply it to data not used in the model's construction". Despite this, they perform only a very basic comparison of one year out-of-

[29] The ABS factors of the FH7 model are discussed further in Section 4.4 and mathematical representation of the model is given in Section 5.1.1.

sample return forecast for four hedge fund indices without any statistical testing[30]. Furthermore, no rigorous out-of-sample test of the FH7 model has been performed yet in any other study. This thesis fills this gap in the literature and conducts out-of-sample statistical testing of the FH7 model as well as other linear and nonparametric models.

3.1.3.2 Option-Based Factor Models

Although the FH7 model is the most widely known hedge fund pricing model, there are at least two other approaches to modelling hedge fund nonlinearities. One of them is known as the option-based factor model, proposed originally in the studies by Agarwal and Naik (2000c, 2004) and later refined by Amenc et al. (2010) and Diez de los Rios and Garcia (2011). Agarwal and Naik (2004) characterize systematic risk exposures of hedge funds using buy-and-hold and option-based strategies:

$$\begin{aligned} R_p = \quad & \alpha + \beta_1 R_m + \beta_2 \max(R_m - k_1, 0) + \beta_3 \max(R_m - k_2, 0) \\ & +\beta_4 \max(k_3 - R_m, 0) \; + \beta_5 \max(k_4 - R_m, 0) + \varepsilon \end{aligned} \tag{3.2}$$

In this model option-based factors (i.e. terms with the $\max$ function) represent returns of the strategy of buying and selling at-the-money (ATM) and out-of-the-money (OTM) European call and put options on the S&P 500 composite index.

The idea of using options in the asset pricing framework is not new. Henriksson and Merton (1981) were the first to suggest using options to explain the performance of managed portfolios. In their model an active fund manager makes a forecast of the market movements and attempts to adjust asset allocation by switching between two discreet

[30] The authors replicate results out-of-sample for one year. However, the only statistic they report is the annual return forecast for four broad hedge fund indices from different data providers. The difference between the forecast and actual return of three equal-weighted indices as reported is below 1%, and is around 2.35% for an asset-weighted index. Based on these figures and without any statistical test it is hard to make any conclusions about model performance.

levels of systematic risk: an up-market value of beta when the forecast is positive and a down-market value beta when the forecast is negative. Henriksson and Merton (1981) show that in such a context, the fund's total return may be viewed as the sum of the return on the market and on a put option on the market. Mathematically the optimal payoff of this strategy which Fung and Hsieh (2001) call as a Primitive Market Timing Strategy (PMTS) equals the absolute value of the difference between the initial and ending asset prices, ignoring option costs:

$$PMTS = \left|S_{end} - S_{begin}\right| \tag{3.3}$$

The payoff of a PMTS in Equation (3.3) resembles the payoff of a PTFS in Equation (3.1). However, they are different in that the PMTS payoff depends only on initial and ending asset prices, while the PTFS payoff depends on the whole path of the asset price during the time period.

In the spirit of Henriksson and Merton (1981), several studies have focused on using option contracts to characterize nonlinearities (Breeden & Litzenberger, 1978; Glosten & Jagannathan, 1994). Glosten and Jagannathan (1994) for example suggest approximating the payoff on a managed portfolio using payoffs for a limited number of options on a suitably chosen index portfolio and evaluating the performance of a managed portfolio by finding the value of these options. In other words, Glosten and Jagannathan (1994, p. 159) propose the inclusion of "excess returns on certain selected options on stock index portfolios as additional 'factor excess returns'".

Agarwal and Naik (2004) apply the approach of Glosten and Jagannathan (1994) to model the nonlinear risks of hedge funds. They employ a stepwise regression procedure and an F-test to identify the set of relevant option contracts, whilst exogenously setting the option parameters (e.g. strike price). The results reveal that payoffs on a large number of equity-oriented hedge fund strategies resemble those from writing a put option on the equity index. For instance, the event arbitrage index shows significant factor loading corresponding to writing an OTM put option on the S&P 500 index. The nonlinear pattern can also be attributed to the risk of deal failure. When markets are down a larger fraction of corporate deals fail and the strategy incurs losses. But the profits are not related to the extent to which the market goes up. Thus, such a payoff resembles the payoff of a naked option on the market.

To confirm that option-based factors represent true economic risks of different hedge fund strategies, Agarwal and Naik (2004) conduct an out-of-sample test for both hedge fund indices and individual hedge funds over the period from July 2000 to December 2001. In general, the difference between the indices and replicating portfolios from the model is 94 basis points for TASS indices and 24 basis points for HFR indices, but both are statistically insignificant in all except one case. The replicating portfolios also explain on average 26.7% (median 22.5%) of variation in out-of-sample returns of individual HFR funds and 27.2% (median 22.6%) of variation in the out-of-sample returns of individual TASS funds.

Agarwal and Naik (2004) conclude that the option-augmented model is able to capture the dominant economic risk exposures of hedge funds, which often have nonlinear form. Therefore, nonlinear option-like payoffs are not restricted only to trend-following funds, as in Fung and Hsieh (2001), but are an integral feature of payoffs in a wide range of hedge fund strategies.

The approach and testing methodology in Agarwal and Naik (2004) suffers from several limitations. The first criticism is related to an a priori choice of option contracts and the variable selection procedure. Given the myriad of hedge fund strategies funds do not hold the same portfolio of options on the same underlying asset and the same strike price. Furthermore, as Diez de los Rios and Garcia (2011) point out, the sequential procedure of adding and deleting option-based factors which have non-normal distributions makes it impossible to rely on standard statistical inference such as the F-test for variable selection. Consequently, Diez de los Rios and Garcia (2011, p. 196) argue that due to ad hoc choice of the variables and their parameters combined with the use of an invalid statistical testing theory "the nonlinear pattern in hedge fund returns found in previous papers may just be a statistical artefact".

Diez de los Rios and Garcia (2011) partially rectify the abovementioned shortcomings in the work of Agarwal and Naik (2004). Specifically, they correct a statistical testing methodology and develop a data dependent procedure for automatic selection of option's strike price, as opposed to assuming it exogenously. However, similar to Agarwal and Naik (2004) only one option-based factor on equity market is included in their model. Their refined econometric methodology leads to surprising results. Linear specification tests indicate that there is statistical support for rejecting linearity in three hedge fund styles out of ten. Only in the Event-Driven, the Managed Futures, and the Fixed-Income Arbitrage styles the model with one option-based factor has significantly higher R^2 coefficient than the model without this factor. This conclusion differs from that in Agarwal and Naik (2004), who find evidence of nonlinearities in most equity-related styles. At individual fund level nonlinear risk exposure patterns are supported statistically for only one fifth of funds. Overall, statistical evidence of nonlinearities in Diez de los Rios and Garcia (2011) is not as overwhelming as in other studies.

The second line of criticism of Agarwal and Naik (2004) study is related to the lack of model testing and comparison with other simple linear alternatives. It is important to compare the performance of an option-augmented model with a more simple linear regression model to understand whether the impact of option-based factors is statistically and economically significant, and if the inclusion of these factors is justified. Since hedge funds' risk factors are not known with certainty[31] there is more than one set of correlated factors which can produce similar result. When the payoff set is expanded to include option-like payoffs, the problem becomes even more difficult. It is possible that a hedge fund which has several linear exposures, will also exhibit a nonlinear correlation with another factor due to nonlinear relationship between the factors. Accordingly, as Fung and Hsieh (2004b, p. 78) put forward a practical guiding principle one could adopt in refining a hedge fund pricing model should be: "given the same level of explanatory power statistically, the set of asset-based style factors that offers the most direct link to conventional asset class indexes is to be preferred". Following this principle, without first confirming that the option-augmented model provides an improvement over the conventional linear factor models, it becomes hard to ascertain the role of option-like exposures in the return-generating process of hedge funds.

Amenc et al. (2010) recognize and address this important limitation in the work of Agarwal and Naik (2004). Amenc et al. (2010) question the efficiency of heuristic option portfolios in hedge fund return modelling. They argue that although the introduction of arbitrary option portfolios can improve the in-sample explanatory power of the model, nothing guarantees

[31] See Section 4.4 for the discussion on hedge fund risk factors.

that the chosen underlying assets and their parameters accurately represent the true state-dependent factor exposure of hedge fund managers.

Following the approach developed in Diez de los Rios and Garcia (2008), Amenc et al. (2010) perform an out-of-sample test of the linear model, the option augmented model and two conditional models based on Markov-regime switching approach, as well as a Kalman filtering approach. The study yields several important findings. Firstly, out-of-sample model fit does not vary significantly across different factor model implementations. Secondly, the option augmented model performs poorly out-of-sample, when compared to the linear model. With the exception of the Long-Short category, for which the performance of the two models is equivalent, option augmented model has consistently higher tracking error and lower correlation compared to the corresponding linear model. The authors attribute the negative effect of option-based factors on the out-of-sample fit to estimation risk. Thirdly, the other dynamic models do not generate a better quality of fit than the linear model. The authors' conclusion is that nonlinear models, which are less parsimonious than their linear counterparts, do not necessarily lead to improved out-of-sample model performance. Thus, due to lack of empirical evidence on superior performance of models accounting for nonlinearities the question about the presence of nonlinear risk in hedge fund strategies remains open.

3.1.3.3 Threshold Linear Regression Model

One of the significant constraints in the option-based model of Agarwal and Naik (2004) in Equation (3.2) is the assumption of a single partition in the factor payoff space; the payoff function of each option-based factor has a single break point which corresponds to the strike price of the option. This constraint substantially reduces the range of possible payoffs which can be modelled. In an attempt to relax the assumption of the fixed number of partitions Giannikis and Vrontos (2011) propose a flexible threshold risk factor model:

$$R_t = \alpha + \sum_{i=1}^{K} \left[\sum_{j=1}^{p_i} \beta_{i,j} f_{i,t} I(f_{i,t} \in P_{i,j}) \right] + \varepsilon_t \qquad \textbf{(3.4)}$$

where R_t is the hedge fund excess return at time t, α is the intercept term of the model, $f_{i,t}$, $i = 1, .. K$ is the excess return of the ith factor at time t, p_i is the number of non-overlapping partitions $P_{i,j}$ of risk factor f_i which are defined by $p_i - 1$ thresholds on f_i, $\beta_{i,j}$, $i = 1, .. K$, $j = 1, .. p_i$ are the factor loadings associated with factor i, ε_t is the error term at time t, I is an indicator function such that $I(f_{i,t} \in P_{i,j}) = 1 * (f_{i,t} \in P_{i,j}) + 0 * (f_{i,t} \notin P_{i,j})$. The model (3.4) permits for unknown number of thresholds in every risk factor that affects hedge fund returns. Identification of significant pricing factors and determination of the number and values of thresholds is incorporated into the estimation step. Bayesian approach and the Markov Chain Monte Carlo (MCMC) stochastic search algorithm are used for model estimation and selection of variables and thresholds.

The results of Giannikis and Vrontos (2011) study suggest that different hedge fund strategies exhibit nonlinear relations to different risk factors. Nonlinearities are observed in twelve hedge fund styles out of thirteen examined. In some styles (e.g. the Quantitative Directional and the Fixed Income Corporate) the model identifies multiple threshold values, indicating that option-based models with one partition may indeed lack the flexibility to capture complex hedge funds' payoff.

Importantly, the authors carry out an out-of-sample analysis to examine whether the threshold model outperforms the simpler pricing models in terms of predictive ability. The results show that in nine to eleven out of the thirteen hedge fund styles the threshold regression models achieve better performance than the linear model as measured by predictive log score.

Overall, Giannikis and Vrontos (2011) takes a step forward in understanding and modeling nonlinear risk in hedge funds. Firstly, it provides evidence of nonlinearities in most of the hedge fund styles. Secondly, it suggests that the reason for the failure of option-based models in an out-of-sample test (Amenc et al., 2010) is likely to be due not to a lack of nonlinearities (Diez de los Rios & Garcia, 2011), but rather to the inability of option-based models to deal with the complex risk exposures of hedge funds. Thus, more flexible approaches, such as a threshold regression model and nonparametric models, are needed to model nonlinearities.

Nevertheless, although the results of Giannikis and Vrontos (2011) are important, the study has several limitations. It does not shed light on the economic significance of nonlinear effects. For instance, the predictive log score measure used to compare threshold models with a linear model in an out-of-sample replication test is not as easy to interpret as a conventional tracking error statistic commonly used by investors to gauge the tracking ability of a model. Also, the authors do not compare the results of the threshold model with other existing models, such as the FH7 model and the option-based model of Agarwal and Naik (2004).

3.1.4 Other Empirical Evidence of Nonlinearities

This section discusses further empirical evidence of hedge fund nonlinear risk exposures. The results from the literature are summarized in Table 3.2.

Mitchell and Pulvino (2001) investigate the return generating process in risk arbitrage funds. They find that returns to risk arbitrage strategies are similar to those obtained from selling uncovered index put options. For example, the returns of funds that try to exploit arbitrage opportunities arising from merger and acquisition (M&A) transactions, are positively correlated with market returns in severely depreciating markets, but uncorrelated with market returns in flat or appreciating markets. Typically, after the announcement of a merger or acquisition deal, the target company's stock trades at a discount to the price offered by the acquiring company (see, for example, Larcker and Lys (1987), Baker and Savaşoglu (2002), Jindra and Walkling (2004)). Because most announced M&A deals are successfully consummated[32], return on a merger arbitrage strategy depends on the initial arbitrage spread between the target's stock price and the offer price, and not on overall stock market returns. During severe market downturns however, risk arbitrage returns may be positively correlated with the market because in a depreciating market, the probability of deal failure is likely to increase. Thus, as the analysis of Mitchell and Pulvino (2001) suggests, hedge funds exploiting the merger arbitrage strategy will generate returns with an asymmetric pattern that resembles the payoff of a short option position.

Chen (2007) and Chen and Liang (2007) examine market timing ability of hedge funds from various categories. As demonstrated by Treynor and Mazuy (1966) market timing is a type of dynamic strategy that adjusts risk exposures according to market forecasts and delivers call option-like payoffs. Therefore, evidence of market timing ability of hedge fund managers may suggest nonlinear patterns in risk exposures[33]. Chen (2007) and Chen and Liang (2007)

[32] According to Officer (2007) the completion rate of all mergers is 78%.

[33] The converse statement may not be necessarily true; nonlinear risk-return profile does not necessarily mean successful market timing ability; market timing is one of the sources of nonlinearities, other sources include, for instance, derivatives trading (see Section 3.1.2).

find that two categories of hedge funds, the Convertible Arbitrage and the Fixed Income Arbitrage, exhibit significant timing ability, whilst three others, the Event Driven, the Emerging Markets and the Global Macro, show significant negative timing in their respective focus markets. At the individual fund level, only 5-7% of funds show significant positive timing ability whilst the same numbers of funds demonstrate significant negative timing ability. Comparing these figures with an estimate of the total number of funds with nonlinearities in Diez De Los Rios and Garcia (2011) of around 20% (see, Section 3.1.3.2) it can be concluded that dynamic timing strategies account for around half of all nonlinear effects, while the rest of the nonlinearities can be attributed to other sources including derivatives trading.

Patton (2009) investigates market-neutrality of equity-market neutral funds using a variety of different definitions of "neutrality". The test on mean neutrality using a third-order polynomial is rejected for 28% of funds, while mean neutrality on the downside is rejected for 20% of funds. These results indicate that although some of these funds may appear to be market neutral with no apparent linear risk exposures, they cannot be considered truly market neutral, because of higher order correlation with market risk factors. The study also highlights the issue that standard risk assessment and performance management tools can be biased, as they do not account for hedge fund nonlinearities.

3.1.5 Research Question 1: Nonlinearities in Hedge Fund Indices

In summarizing the literature detailed above, the following points can be noted. There are theoretical and empirical arguments supporting the notion of asymmetric patterns in hedge fund risk exposures. The extant literature documents a wide range of nonlinear anomalies across various hedge fund categories and strategies. Several approaches have been proposed to model nonlinearities. Among them are the seven-factor Fung and Hsieh (2004b) model, the option-based factor model (Agarwal & Naik, 2004) and a threshold linear regression model (Giannikis & Vrontos, 2011). However, there is a concern about the robustness of these models and potential data snooping bias in results. As known in statistics and acknowledged in hedge fund studies (Fung & Hsieh, 2004b), the best way to gauge model usefulness is an out-of-sample test. The only study in which a rigorous out-of-sample test of linear and some of nonlinear models has been performed has failed to support superior performance of models accounting for nonlinearities comparing with a linear multi-factor model (Amenc et al., 2010). The seven-factor Fung and Hsieh (2004b) model also has not been adequately tested out-of-sample. Accordingly, existing statistical evidence of nonlinearities is not sufficient and requires further investigation. To address the issue and obtain a robust statistical evidence of nonlinearities the first research question is postulated as follows:

(RQ1): Do hedge fund style portfolios have nonlinear exposure to systematic risk?

More specifically this question can be split into two parts:

(RQ1.1): Is there any statistical evidence of nonlinear effects in systematic risk exposures in hedge fund style portfolios in-sample?

(RQ1.2): Can nonlinear risk exposures in hedge fund style portfolios be adequately modelled and confirmed out-of-sample?

The main focus in these questions is on nonlinearities in hedge fund styles portfolios. The next section will outline research questions related to analysis of nonlinearities in individual funds.

To answer these questions this thesis advocates for a nonparametric approach to modeling nonlinearities. A nonparametric approach is as an extension of previous models, such as the option augmented model with one threshold in each factor, and a piecewise linear model with multiple thresholds. The study of Giannikis and Vrontos (2011) suggests that flexibility of the model is indeed important for accurate estimation of nonlinearities. Hence, an examination of nonparametric models is warranted.

3.1.6 Research Question 2: Nonlinearities in Individual Hedge Funds

Although the analysis of nonlinear risk exposures at portfolio level has an important advantage due to less noise in aggregated data, aggregation can lead to a biased picture. Diez de los Rios and Garcia (2011) argue that aggregation of individual funds into style portfolios may create either a smoothing effect, which will mask nonlinearities existing in individual funds' exposures, or, conversely, create spurious nonlinear structures that are not present in individual funds. Thus, the second research question in this thesis is related to investigation of nonlinearities at the fund level. It is formulated as follows:

(RQ2.1): Do individual hedge funds have nonlinear exposures to systematic risk?

Majority of the studies listed in Table 3.2 provide empirical evidence of nonlinearities at the portfolio level. The most relevant study which examines nonlinear exposures in individual funds is the study of Diez de los Rios and Garcia (2011). The author finds that nonlinear features are present and supported statistically in only one-fifth of individual funds. This is quite unexpected result given the ample evidence of nonlinearities in hedge fund portfolios in other studies. It suggests that nonlinear features are not a statistical reality for many funds and conclusions based only on indexes can be misleading.

Diez de los Rios and Garcia (2011) also perform a valuation of nonlinear features. In their setting nonlinearities are modelled with options which are valued using the Black–Scholes option pricing framework. The results reveal that only one fund out of two provides significant positive performance to its investors. In addition, there is a cross-sectional variation in the estimated money-ness of options across individual funds. These findings emphasize that proper statistical testing and disaggregation are important to draw a realistic picture of performance in the hedge fund industry.

The question about the value generated by nonlinear risk exposures in hedge fund strategies is a very important one. Nonlinear effects in risk exposures are one of the main features that distinguish risk-return profiles of hedge funds versus mutual funds. Traditional long-term strategies involving investments in shares and bonds employed by mutual funds entail a linear relation between the beta and expected returns. Dynamic trading strategies of hedge funds, in contrast to buy-and-hold strategies, result in nonlinear patterns of risk exposures. Nonlinear exposures per se however provides no guarantee that a fund extracts profits from alpha rather than systematic risk. If nonlinear effects are driven by nonlinear systematic risk exposures, for example, derivatives holdings in hedge funds' portfolios, then their value will be commensurate with the amount of risk taken. On the other hand, if nonlinearities reflect, for instance, market timing abilities of a manager, then these features may have a positive value to investors.

Extant empirical studies have delivered mixed results. Peltomäki (2009) investigates the relationship between the complexity of derivative strategies and the performance and risk characteristics of hedge funds. The author presents evidence that the complexity of derivative strategies is positively related to the increased probability of large losses and weaker performance. Chen (2011) also studies derivative use and risk taking in hedge funds and reaches opposite conclusions. He finds that derivative users on average exhibit lower fund risks (market risk, downside risk, and event risk) and their after-fee risk-adjusted performance is similar to the performance of nonusers. Both the studies of Peltomäki (2009) and Chen (2011) rely on self-reported information on fund derivative usage. This data has not been scrutinized in the literature as much as other hedge fund data and their accuracy and credibility remains questionable.

The discussion about the differentiated ability of funds with and without nonlinear risk exposures to generate value for investors leads to the next research question:

(RQ2.2): Do funds with nonlinear exposures to systematic risk outperform funds with linear risk exposures and funds without significant exposure to systematic risk?

In this question funds with nonlinear risk exposures are compared not only with linear funds (i.e. funds with linear exposures), but with funds without any significant exposures as well. This group without significant exposures is important because based on recent studies it has been estimated to be quite a large category. Bollen (2013) performs factor analysis on a broad sample of hedge funds and finds that for one third of the funds their R^2 coefficient in the regression model is not significantly different from zero. Accordingly, the author classifies funds into "positive R^2" and "zero R^2" groups based on the magnitude of R^2 coefficients and critical values of the R^2 derived via a simulation procedure. Although "zero

R^2" funds cannot be regarded as completely systematic risk-free funds, since factor models do not capture perfectly all sources of systematic risk, they are found to have substantially lower level of systematic risk than "positive R^2" funds. Furthermore, these funds feature lower volatilities, higher risk-adjusted performance and higher alphas than other funds. The low-R^2 property also however increases the probability of a fund failure, suggesting the presence of omitted or extreme nonlinear risk exposures.

Finally, if a significant relationship exists between the form of funds' exposures and its performance, it is important to evaluate the persistence of these exposures as well. For example, it is well known that hedge fund investors are mostly unable to take advantage of the information regarding a fund's historical performance because the performance often lacks long-term persistence. A similar question arises therefore in regards to the persistence of nonlinearities, that is, whether knowledge about the past profile of funds exposures can be exploited for investment decision making in the future. Accordingly, the last research question related to the analysis of nonlinearities in individual funds is postulated as follows:

(RQ2.3): Does the form of funds' exposures (i.e. linear and nonlinear) persist?

3.2 Nonlinear Hedge Fund Replication

As discussed in Section 3.1, a significant portion of hedge fund returns stems from funds' exposures to systematic risk factors, i.e. alternative beta. In a diversified hedge fund portfolio up to 80% of monthly return variation can be attributed to systematic risk factors (Fung & Hsieh, 2004b). Systematic risk exposures of hedge funds may have a linear or a nonlinear form depending on fund's holdings and trading strategy. One of the ways to utilize the knowledge about alternative beta in practice is related to the idea of passive hedge fund replication. Academic studies suggest that hedge fund strategies can be replicated via passive investment strategies, since hedge fund returns to a large extent are derived from risk factor premiums (Hasanhodzic & Lo, 2007; Jaeger & Wagner, 2005). However, the success of hedge fund replication depends on the accuracy of hedge fund pricing models and their ability to model linear and nonlinear risk-return relationships. So far no one has proposed a nonlinear hedge fund replication model in the literature. Accordingly, the third part of this thesis focuses on application of nonparametric models developed in the first part to the task of hedge fund replication.

The next three sections elaborate the idea of replication and review relevant literature. Section 3.2.1 explains the rationale, the concept and main advantages of passive hedge fund replication to investors; Section 3.2.2 reviews existing approaches to replication; Section 3.2.3 explains the difference between the two types of benchmarks used in replication models; and Section 3.2.4 formulates the third research question. The details of all academic studies discussed in these sections are summarized in Table 3.3.

Table 3.3 Hedge Fund Replication and Performance Evaluation of Investable and Non-Invertible Hedge Fund Indices

Study	Scope	Data	Main result
Géhin and Vaissié (2004)	Overview of the literature on NHFIs[34] and IHFIs		Most hedge fund indices are not representative of the entire investment universe; the investable hedge fund indices available on the market turn out to be nothing more than passively managed FHFs; quality benchmarks cannot be truly representative, since having viable passive alternatives is crucial
Jaeger and Wagner (2005)	Constructing replicating factor strategies (RFS); performance comparison of RFS and NHFIs and IHFIs[a]	March 2003 – August 2005; HFRX and HFRI strategy indices	On average investable HFRX indices substantially underperform non-investable HFRI indices (by 62 bps per month or 7.7% annually); the difference is attributed to selection bias – hedge funds at full capacity (closed) are not included into investable indices; Conversely, RFS substantially outperform all HFRX strategy indices with the exception of the distressed sector; outperformance is likely to be due to high hedge fund fees
Goltz, Martellini and Vaissié (2007)	Construction of investable and representative IFHIs	CISDM (formerly called MAR) database; 1,800 active hedge funds and 600 active CTAs	Style indices constructed with small number of open to investment funds using principal component and factor analysis are found to be representative for various hedge fund strategies. Portfolio of well-chosen funds adequately captures the returns characteristics of a large set of funds (except Equity Market Neutral category)
Hasanhodzic and Lo (2007)	Factor analysis of individual hedge funds; construction and performance comparison of linear clones and NHFIs	February 1986 – September 2005; 1610 hedge funds from Credit Suisse/TASS database; the funds are used to construct equal-weighted strategy indices	Significant fraction of funds' expected returns and volatility can be captured by common factors corresponding to liquid exchange-traded instruments; performance of linear clones is often inferior to their hedge fund counterparts, though it is well enough considering their lower cost, scalability and transparency
Wallerstein, Tuchschmid and Zaker (2010)	Performance evaluation of HFRS	March 2008 – May 2009; Long Barclays Alternatives Replicator Index; Credit Suisse Long/Short Equity Replication Index; Credit Suisse Inverse Long/Short Equity Replication Index; CON-DB Alternative Return Fund; Goldman Sachs-Absolute Return Tracker Index; ICE-Alternative Beta Fund; IC-Salto Index; IC-Verso Index; JP Morgan Alternative Beta Index; Merrill Lynch Factor Index; Societe Generale Alternative Beta Index; Deutsche Bank Absolute Return Beta Index; FLC-Alternative Beta Fund; IQ-Hedge Composite Beta Index; RYD-Multi-Hedge Strategies Fund; Morgan Stanley Altera Index; PG-Alternative Beta Strategies Index; AC-Statistical Value Market Neutral 7 Vol Fund; DGAM-Synthetic Alternative Investment Fund;	HFRS are highly correlated with NHFIs (correlation varies across products from 0.70 to 0.90) and overall deliver competitive performance relative to hedge funds; monthly excess return of HFRS over HFRI Fund of Funds Index is not significantly different from zero for 8 clones out of 11, positive for 2 clones and negative for 1 clone
Tuchschmid, Wallerstein and Zaker (2010)	Update of Wallerstein et al. (2010)	April 2008 – October 2010; same data as in Wallerstein et al. (2010) plus another three replication products	One third of HFRS outperform HFRI composite index (based on Sharpe ratio) and combined they outperforms the HFRI fund of funds index by 1.1% annually with similar levels of volatility; one

[34] NHFI – Noninvestable Hedge Fund Index; IHFI – Investable Hedge Fund Index; RFS – Replicating Factor Strategy, i.e. replicating strategy based on factor approach; HFRS – Hedge Fund Replicating Strategy , i.e. replicating strategy based on any approach and traded in the market in the form of a commercial product

			HFRS out of 15 has positive and one negative and statistically significant alpha (relative to the seve-factor Fung and Hsieh (2004b) model augmented by emerging markets equity return premium)
Heidorn, Kaiser and Voinea (2010)	Performance comparison FoFs, NHFIs, IHFIs, and HFRS offered in the market with particular focus on NHFIs and IHFIs	IHFIs: in total 111 indices from January 2002 to October 2009 including Credit Suisse/TASS AllHedge Index, Credit Suisse/TASS Blue Chip Index, ARIX Composite Index, Greenwich Investable Hedge Fund Index, HFRX Global Hedge Fund Index, RBC Hedge 250 Index; FHFs: 525 FoFs from Credit Suisse/TASS; NHFIs: Credit Suisse/TASS Hedge Fund Index, Greenwich Global Hedge Fund Index, HFRI Fund Weighted Composite Index; HFRS: 19 replication funds or indices, of which 12 are based on factor analysis, 4 are rules-based, and 2 are based on distribution approach (same as in Wallerstein et al. (2010))	IHFIs are representative of the hedge fund universe; they have high correlations with NHFIs (>0.9), average beta of 0.98 and negative alpha across all indices; based on risk-adjusted measures IHFIs underperform NHFIs; in the best case scenario IHFS outperform FoFs and HFRS, but in the worst-case scenario underperform both investments; overall IHFIs constitute solid alternative to FoFs
Giamouridis and Paterlini (2010)	Construction of RFS based on Lasso regression, Ridge regression and standard stepwise techniques with AIC and BIC variable selection; performance comparison with three commercially available RFS	February 1990 – July 2008: HFR Equity Hedge, Event Driven, Macro, Relative Value, Emerging Markets, Fund of Funds Composite and Fund Weighted Composite indices; February 2003 – July 2008 Citi's HARP Index, Deutsche Bank's Absolute Return Beta Index, and Merrill Lynch's Factor Index	Regularized hedge fund clones have similar out-of-sample performance to standard constrained regression model, but lower portfolio turnover. Clones based on Lasso and Ridge models are attractive relative to both their benchmark hedge fund index and to selected commercially available hedge fund clone products that use proprietary construction techniques.
Boigner and Gadzinski (2013)	Performance comparison and factor analysis of IHFI and NHFI	September 2004 – April 2010; NHFI: Credit Suisse/TASS and HFRI hedge fund strategy indices; IHFI: Credit Suisse AllHedge indices	All IHFIs except two strategies perform worse than their corresponding hedge fund benchmarks regardless of the sample period based on several performance measures (Sharpe, Omega ratio and Farinelli-Tibiletti ratio). Managed Futures and Global Macro IHFIs exhibit superior performance measures relatively to NHFIs, outperform all other IHFIs and offer little exposure to systematic risk factors

3.2.1 Rationale, Concept and Advantages

In theory investors who want to diversify a traditional portfolio of stocks and bonds by adding exposure to hedge funds have three ways to allocate their capital. Firstly, investors can perform due diligence and performance analysis of hedge funds and select the fund or several funds, which they think will perform well over the investment horizon. However, it is a very difficult task to select fund managers. For instance, Do, Faff, Lajbcygier, Veeraraghavan, and Tupitsyn (2014, forthcoming) examine the flow-performance relationship in CTA funds and find little evidence to support the notion of smart choice. CTA funds which attract more funds subsequently do not generate superior risk-adjusted returns, particularly at a long horizon (one year). Similarly Baquero and Verbeek (2009) find that investors fail to predict future fund returns; however investors are relatively successful in their divestment strategies, responding quickly and appropriately by de-allocating from any persistent losers. The reason behind these findings is two-fold. On the one hand, alpha is scarce, because active management is a zero-sum game; every alpha trade results in both a winner and a loser (Fama & French, 2010; Sharpe, 1991). Thus, only a few hedge funds generate alpha (Amin & Kat, 2003; Capocci & Hubner, 2004). Also, hedge fund performance shows little persistence (at least at long horizons)[35]. As a result, hedge fund investors are unlikely to get benefits from past performance information and selection of fund managers is complicated.

The second option for potential hedge fund investors is to delegate the job of manager selection to a professional fund of funds manager. However, fund of funds managers also show little skill at picking skilled managers. For instance, average fund of funds did not

[35] See Eling (2009) for a review of 25 hedge fund performance persistent studies,

deliver positive alpha between 2000 and 2004 (Fung, Hsieh, Naik, & Ramadorai, 2008). Moreover, when investing in fund of funds investors have to pay the double layer of fees to the fund of funds manager and underlying funds, which further erodes profits and makes hedge fund investments more expensive and less attractive.

The last option is to diversify the idiosyncratic risk of individual funds by investing into a broad portfolio of hedge funds, e.g. a hedge fund style index. Similar to index funds like the Vanguard S&P 500 fund which tracks the S&P 500 equity index, hedge fund indices are supposed to track the performance of aggregate hedge fund portfolios. However, few investable hedge fund indices exist in the market today and little is known about their performance characteristics and tracking properties (Géhin & Vaissié, 2004; Wallerstein et al., 2010). In general, the very idea of hedge fund indexing is complicated and not as straightforward as in case of equity or bond index funds. The major problem is that the bulk of hedge funds are closed to new investors and those which are open implement restrictions on capital in- and outflows[36]. Therefore, investable hedge fund indices comprising a broad portfolio of funds suffer from selection bias and lack representativeness of the hedge fund universe (Géhin & Vaissié, 2004; Jaeger & Wagner, 2005). Another problem is that akin to fund of funds investable hedge fund indices imply a double layer of fees, as they invest directly into hedge funds. Therefore, investable hedge fund indices turn out to be nothing more than passively managed funds of funds (Géhin & Vaissié, 2004)[37].

[36] As estimated in Section 8.1 only 14% of funds in the TASS Live database were open to new investors as of September 2010

[37] See the discussion on investable and non-investable indices in Section 3.2.3

It is necessary to clarify that despite poor long-term hedge fund performance[38], some strategies employed by hedge funds can still be attractive to investors. The reason, as Fung and Hsieh (2007) suggest, is that unlike the mutual fund industry, there is no evidence of consistent negative alpha in net-of-fee returns of hedge funds. In line with the rational model of active portfolio management by J. B. Berk and Green (2004) hedge fund managers are able to find alpha, but alpha is ultimately consumed by high fees. Empirical estimates of gross alpha support this view, as alpha before fees is as much as twice higher than alpha net of fees (Brooks et al., 2007).

Accordingly, if hedge fund fees could be eliminated or at least reduced to levels comparable with other traditional funds via passive hedge fund replication strategies, investors would benefit from achieving hedge fund like returns in a cost-efficient way. The idea of hedge fund replication or cloning has been proposed in the studies by Fung and Hsieh (2001), Amin and Kat (2003), Jaeger and Wagner (2005) and Hasanhodzic and Lo (2007). Hedge fund clones refer to passive strategies tracking the returns of hedge fund portfolios and executed cheaply with liquid financial instruments (Tupitsyn & Lajbcygier, 2013). The difference between hedge fund clones and investable hedge fund indices is that the former do not require direct hedge fund investing. Clones use futures, ETFs and other liquid instruments to replicate dynamically systematic risk exposures of hedge funds, whereas investable indices represent actively managed portfolios of hedge funds.

Hedge fund clones have several advantages over their real counterparts. Firstly, they eliminate hefty incentive fees. Since clones represent passive strategies performance based

[38] For example, Dichev and Yu (2011) shows that from 1980 to 2008 the dollar-weighted net-of-fees return of a value-weighted portfolio of hedge funds was lower than the return on the S&P 500 Index and only marginally higher than the risk-free rate of return

fees are substituted with a fixed fee aligned with operational expenses and transaction costs associated with clone construction. Secondly, clones by construction represent liquid investments. Enhanced liquidity enables easy valuation and allows quick redemption of funds at any time based on market value of underlying securities. Thirdly, replication strategies are transparent to investors. Investors can access information on portfolio composition at any time. Lack of transparency is one of the main issues of the hedge fund industry (Hedges, 2005). Fourthly, clones are virtually free from capacity constraints as long as they trade in deep and liquid markets. Capacity constraints are important because they affect the ability of hedge funds to grow and generate returns (Naik et al., 2007).

Considering all the advantages of hedge fund replicators relatively to other ways of investing into hedge funds and taking into account other appealing features of the clones, there is a strong motivation to explore the area in more detail. In particular, it is interesting to investigate whether research on hedge fund nonlinearities can be used to improve existing linear replication models of alternative beta.

The next section discusses the current state of research in this field.

3.2.2 Replication Models

Three approaches to hedge fund replication have been proposed in the academic literature: rule-based replication (Agarwal, Fung, et al., 2011; Fung & Hsieh, 2001, 2011; Mitchell & Pulvino, 2001), the distributional approach (Kat & Palaro, 2006) and the factor-based replicating approach (Hasanhodzic & Lo, 2007; Jaeger & Wagner, 2005). Rule-based replication approaches attempt to execute trading schemes similar to hedge fund strategies by following a set of predetermined rules for managing assets. For instance, Fung and Hsieh (2001) reverse engineer and replicate the trend following strategy, a common strategy employed by systematic CTAs (see, Section 3.1.3.1); Mitchell and Pulvino (2001) propose a primitive merger arbitrage strategy that mimics typical activities of merger arbitrage funds; Agarwal, Fung, et al. (2011) implement a buy-and-hedge convertible bonds strategy to replicate returns of convertible arbitrage funds. These rule-based replication strategies essentially advocate investments in the same assets as those traded by hedge funds, but draw on rules to govern the investment process instead of involving an active manager. The problem with the approach is that rules are often heuristic, since parameters are chosen arbitrarily; moreover, the resulting strategies can be as complex as hedge fund strategies themselves undermining the key rationale behind the replication which is simplicity and transparency. Therefore, rule-based replication process can hardly be considered truly passive.

The distributional approach developed by Kat and Palaro (2006) though considered in the literature as one of the replication approaches is not really a replication method. Rather it can be described as an approach that attempts to realise comparable statistical properties without consideration of how the fund itself trades. In contrast to other replication approaches the objective of this method is not the approximation of the month-to-month returns of a hedge fund portfolio, but replication of distributional properties of hedge funds' returns, with the notable exception of the mean return. The rationale behind this concept rests on the argument that hedge funds are attractive investments mainly due to specific properties of their return distribution. In other words, the only important feature of a hedge fund is its entire return distribution, and the sequence of returns is irrelevant. Empirical tests of this approach reveal a number of important shortcomings. As mentioned above the method does not attempt to replicate the mean of the return distribution; the mean return depends on the basis asset which is used in the replication process[39]. Accordingly, the average return of the clone typically deviates substantially from the average return of the benchmark. Also, the reasonable quality of replication of the second and higher order moments can be achieved only if the time horizon of the investment is very long (around eight years or longer, as shown in Amenc, Gehin, Martellini, and Meyfredi (2007)). Due to these limitations the distributional approach has not gained much popularity in the literature and among practitioners.

Finally, the third approach advocated in this thesis is known as the factor-based replication. Due to its relative simplicity, objectivity, transparency, and intuitiveness compared with the previous two approaches this method is the most popular and easiest to implement. Its theoretical foundation rests on a linear multi-factor model, given below:

$$R_{i,t} = \alpha_i + \sum_{j=1}^{N} \beta_{i,j} F_{j,t} + \varepsilon_{i,t} \tag{3.5}$$

where R is fund's (excess) return, α is the abnormal return, β is the factor sensitivity, F is the risk factor proxy, and ε is the error term, which is assumed to be normally distributed and uncorrelated to the factors or to its previous realizations. To construct the clone alpha coefficient in model (3.5) is set to zero and beta coefficients are constrained to add up to one. Given these constraints regression coefficients $\beta_{i,j}$ can be interpreted as portfolio weights, and the replicating portfolio can be estimated as follows:

$$R_{i,t}^{Clone} = \sum_{j=1}^{N} \beta_{i,j} F_{j,t} \tag{3.6}$$

[39] For detailed explanation, see Kat and Palaro (2006)

The most popular replication model of the form (3.6) was proposed by Hasanhodzic and Lo (2007) and consists of six factors, which are discussed further in Section 4.4. Hasanhodzic and Lo (2007) apply the model to replicate the returns of individual funds from eleven hedge fund strategies. Their findings suggest that the concept of cloning hedge-fund returns is viable and achievable at least in some hedge fund styles. For certain hedge-fund categories, the average performance of clones is shown to be comparable or above that of hedge funds on both a raw return and a risk-adjusted basis (Equity Market Neutral, Global Macro, Dedicated Short Bias, Managed Future, Fund of Funds). For other categories the clones are less successful (Event Driven, Convertible Arbitrage, Fixed Income Arbitrage, Long-Short Equity, Emerging Markets). Although the authors measure performance characteristics, they do not report any measure of tracking accuracy.

Another version of a linear factor replication model is due to Giamouridis and Paterlini (2010). Unlike Hasanhodzic and Lo (2007) these authors utilize the ridge (Hoerl & Kennard, 1970) and the lasso[40] (Tibshirani, 1996) regressions instead of a linear regression. Both methods involve the optimization of a penalized version of the residual sum of squares (RSS) function. In the ridge regression the penalty term added to the RSS function is proportional to the second norm of the weights, while in the lasso regression it is proportional to the first norm. The lasso regression has an additional advantage over the ridge regression, as it enables automatic variable selection. The coefficients in the lasso model may completely shrink to zero during the optimization procedure, thus effectively performing the variable selection.

[40] Least Absolute Shrinkage and Selection Operator

In theory regularization methods such as the lasso and ridge regressions should lead to more stable estimates of the model parameters in the presence of noise in the data (Brodie, Daubechies, De Mol, Giannone, & Loris, 2009; DeMiguel, Garlappi, Nogales, & Uppal, 2009). In practice this means that the turnover of the replication portfolio should be reduced. The results of Giamouridis and Paterlini (2010) support this notion. Giamouridis and Paterlini (2010) replicate the returns of seven hedge fund categories including a composite index of hedge funds' performance. They find that comparing with the standard linear regression model, which on average requires about one-third of the portfolio to rebalance at each point of time, the turnover of lasso based portfolios drops to about one-fifteenth. Associated benefit in terms of returns is estimated in the magnitude of 1 to about 10 bps per month. Nevertheless, despite the lower turnover, regularized clones do not achieve improvement in an out-of-sample performance comparing with linear clones. Excess returns of regularized and standard linear clones are not significantly different.

The next section discusses an important issue of selecting a benchmark index for replication.

3.2.3 Replication Benchmark: Investable vs Non-Investable Index

The previous section introduces three approaches to hedge fund replication. It also highlights the advantages of the factor-based replication approach including transparency, the intuitive objective of tracking return time series, and feasibility of implementation. Following these arguments, this thesis focuses further only on the factor-based replication approach.

In the study of Hasanhodzic and Lo (2007) replication models are applied to replicate time series of returns of individual hedge funds, while Giamouridis and Paterlini (2010) replicate broad hedge fund style indices. As discussed in Section 3.2.1 investors, are more interested in replicators of aggregate portfolios of hedge funds than clones of individual funds, since portfolios have much less idiosyncratic risk that is difficult to predict and evaluate ex ante. Hedge fund style indices used for replication in Giamouridis and Paterlini (2010) as well as in other studies including Amenc et al. (2010), reflect the performance of all hedge funds within each style; however, returns of style portfolios cannot be realized by investors. These indices can be viewed as theoretical hedge fund benchmarks, because most of their constituents are actually closed for new investors[41]. This issue raises concern as to whether a comparison between investable replication products and non-investable hedge fund indices is appropriate. Indeed, the question is not trivial, because whilst there is ample existing literature covering various characteristics of funds and their effect on performance, few studies analyse differences between those funds which are open and closed for new investments.

Two alternative hypotheses can be put forward in regards to relative performance of open and closed funds (i.e. funds closed for new investments). The first hypothesis is that closed funds comprise more mature funds, which have reached capacity constraints and no longer able to effectively utilize investors' new capital. These funds are not under pressure to grow AUM to generate incentive fees and thus should exhibit a higher degree of risk aversion and lower absolute returns than their younger counterparts striving to attract new funds. The

[41] See footnote 368

alternative hypothesis stems from what Jeremy Duffield[42] coined as the 'Groucho Marx effect'[43]: open funds remain open because they never grow enough due to poor performance and no one is interested to close them.

Empirical studies which touch upon the issue find strong support for the last hypothesis. Investable hedge fund indices severely underperform theoretical benchmarks. Jaeger and Wagner (2005) estimated that the average monthly underperformance of the composite investable hedge fund index relative to the non-investable index was 62 bps monthly or 7.7% annually during 2003-2005. A similar dramatic difference was observed in terms of the risk-adjusted performance. The Sharpe ratio of the composite investable and non-investable indices was 0.05 and 0.69 respectively in 2000-2009, as reported in Heidorn et al. (2010), while the omega ratio, a performance measure which accounts for higher order moments, was also substantially lower for investable indices in all hedge fund categories except the Emerging Markets style in 2004-2010 (Boigner & Gadzinski, 2013). Jaeger and Wagner (2005) explain the severe underperformance of investable indices by a selection or "access" bias. Investable indices do not include all the investable funds available in the market, but only a part of them, which in theory is supposed to be representative of the hedge fund universe, but in practice is biased towards new, unproven, open funds which service providers have access to. In such opaque and non-public markets as those in which hedge funds operate access is not determined by the market price, but by investors' ability to get and keep direct access to individual fund managers. Thus, investable hedge fund indices are essentially a form of fund of funds rather than true index funds. The only difference between the two is

[42] Jeremy Duffield is the former Chairman of Vanguard Investments Australia. He proposed this idea whilst discussing the results of this thesis with the author.

[43] Groucho Marx was a comedian and film and television star, known as a master of quick wit. He was once quoted as saying: "I would not want to belong to any club that would accept me as a member".

in the approach to selection of underlying funds: a fund of funds manager actively searches for alpha and trading talent, while the indexer's goal is to minimize the tracking error, regardless of the alpha and beta decomposition of returns of the underlying funds.

In conclusion to this discussion on investable and non-investable indices, it is noted that it is necessary to examine clones of both types of indices in order to provide more objective comparison of clones and hedge funds. The next section formulates the third research question associated with the idea of nonlinear hedge fund replication.

3.2.4 Research Question 3: Nonlinear Hedge Fund Replication

As explained above hedge fund replicators represent passive investments strategies which aim to match the time series properties and return characteristics of hedge fund strategies. The concept of replication has already been implemented by a number of financial service providers. Wallerstein et al. (2010) identifies 21 replication products as of May 2009 offered by companies including Barclays Capital, Credit Suisse, Goldman Sachs, JP Morgan, Merrill Lynch, Deutsche Bank, Morgan Stanley and others. Unfortunately, Wallerstein et al. (2010) are unable to determine the benchmark index of each replication product, hence they perform only performance evaluation of the clones, rather than investigating tracking ability of the clones. Therefore, little is known to date about the tracking properties of existing commercial replication products.

The replication method used in most of the commercial products is the linear factor based approach, as reported in Wallerstein et al. (2010). Although there is a strong evidence to expect nonlinear patterns of alternative beta (see Section 3.1), nonlinear replication method has not been proposed yet. This gap in the literature motivates the third research question:

(RQ3): Does a nonlinear replication approach outperform a linear factor based approach?

The third research question is relevant to the topic of the thesis. While the first two research questions seek to find statistical evidence of nonlinear patterns in risk exposures of hedge fund portfolios and individual funds, the third research question focuses on investigation of the importance of nonlinear effects from a practical perspective. In theory, nonlinear clones are expected to perform better than linear clones, if nonlinearities are confirmed. However, although nonlinearities may be significant statistically, it is not clear whether their magnitude has a sizable economic effect on performance and tracking properties of the clones. This is exactly the main focus of the third research question.

Furthermore, due to important differences between investable and theoretical indices (see Section 3.2.3), clones of both types of indices should be constructed and evaluated. Accordingly, the related questions are formulated below:

(RQ3.1) Does a nonlinear replication approach outperform a linear factor based approach for non-investable hedge fund style indices?

(RQ3.2) Does a nonlinear replication approach outperform a linear factor based approach for investable hedge fund style indices?

As an additional question not directly related to the topic of this study, but nevertheless a very important issue for practitioners that can be addressed together with the questions above, is a question about relative performance of investable and theoretical indices:

(RQ3.3) Do theoretical non-investable hedge fund indices outperform their investable counterparts?

Chapter 4 Data

This chapter discusses the sources of data used in the thesis, procedures applied to correct for known biases in hedge fund data and variables utilized in the models. Since there are three main research questions in the thesis, three datasets have been constructed. All data sources are presented in Table 4.1.

Table 4.1 Sources of Hedge Fund Data

Research Question	Hedge Fund Dataset
RQ1: Model Selection and Nonlinearities in Hedge Fund Style Portfolios	Credit Suisse/TASS Hedge Fund Indices
RQ2: Nonlinearities in Individual Hedge Funds	Credit Suisse/TASS database on individual hedge funds
RQ3: Nonlinear Hedge Fund Replication	HFRI and HFRX Hedge Fund Indices; Credit Suisse/TASS Hedge Fund Indices

The remainder of the chapter is divided into the following sections. Section 4.1 covers the data on hedge fund indices and individual funds sourced from the Credit Suisse/TASS[44] database. Section 4.2 describes various biases present in hedge fund data and outlines the procedures employed to correct the biases. Section 4.3 covers the data sourced from the HFR, i.e. non-investable hedge fund style indices (HFRI), and investable hedge fund style indices (HFRX). Finally, Section 4.4 elaborates the choice of the independent variables used in the models.

[44] TASS database, thereafter in the thesis

4.1 TASS Data

The primary source of data on hedge funds for the first and second research questions is the Tremont Advisory Shareholder Services (TASS) database. It provides historical information on returns and assets under management of individual funds as well as a wide range of additional fund specific information, including a fund's self-reported style. The TASS database is one the oldest and largest hedge fund databases and it is commonly used in academic research[45].

The data spans from January 1994 to September 2010[46]. Hedge funds in the TASS database are classified into fourteen styles: Emerging Markets, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Fund of Funds, Global Macro, Long-Short Equity, Managed Futures, Multi-Strategy[47], Options Strategy, Other hedge funds, and Undefined hedge funds. The last three styles are commonly excluded from the analysis; they represent not more than 2.5% of the total number of hedge funds in the database. For each of eleven styles TASS calculates a value-weighted hedge fund styles index updated monthly. As pointed out in Table 4.1 hedge fund style indices are used in the first and third parts of this study for examination of nonlinear risk exposures at portfolio level and hedge fund replication.

The dataset with individual funds is used in the second part of the thesis for examination of nonlinearities at fund level. The data are sourced from the TASS 'Live' database containing

[45] The TASS database is used by Fung and Hsieh (1997a, 2000), Liang (2000), Brown, Goetzmann and Park (2001), Lo (2001), Brown and Goetzmann (2003), Agarwal and Naik (2004), Getmansky, Lo and Makarov (2004), Lo, Getmansky and Mei (2004), Malkiel and Saha (2005), Hamza, Kooli and Roberge (2006),Bali, Gokcan and Liang (2007), Kosowski, Naik and Teo (2007), Agarwal, Daniel and Naik (2009), Kang, In, Kim and Kim (2010), Aggarwal and Jorion (2010b), Bali, Brown and Caglayan (2011), Aggarwal and Jorion (2012), Cao, Chen, Liang and Lo (2013), Jorion and Schwarz (2014), and Horst and Salnganik (2014), among others.

[46] This was the latest data available at the time this research was initiated in early 2011

[47] The data for Multi-Strategy style are available since April 1994

active funds and the TASS 'Graveyard' database containing defunct funds. Active funds are funds which are in operation and defunct funds are the funds which have closed, liquidated or stopped reporting to the database for any reason. Several filters are applied to the dataset: funds which (i) do not report net-of-fee returns; (ii) report returns in currencies other than the US dollar; (iii) report returns less frequently than monthly; (iv) do not provide assets under management or only provide estimates; and (v) have fewer than 60 monthly returns are excluded. The minimum requirement of 60-month history is necessary to estimate models. Nonparametric techniques employed for construction of nonlinear models are more data intensive than, for example, ordinary least squared linear regression. The final sample of individual hedge funds consists of 5,580 funds, of which 2,670 are active and 2,910 are defunct.

The next section discusses potential biases in the data and correction procedures.

4.2 Biases in Hedge Fund Data

Since hedge funds report voluntarily to data vendors, hedge fund databases are prone to multiple biases. These biases have been extensively discussed in the literature. They include survivorship bias, instant history or backfilling bias, self-selection bias, stale price bias and multi-period sampling bias (Aiken, Clifford, & Ellis, 2013; Baquero, Horst, & Verbeek, 2005); Brown, Goetzmann, Ibbotson, and Ross (1992); (Fung & Hsieh, 1997b, 2000, 2002a; Getmansky et al., 2004; Liang, 2000; Park, 1995).

Survivorship bias occurs when a hedge fund that no longer reports to the data vendor is excluded from the database. This can cause a serious problem for research, because a large number of funds may be missed due to high attrition rates of hedge funds. Kat and Brooks

(2001) estimate that nearly 30% of newly established hedge funds do not survive the first three years. Brown et al (2001) provide more conservative estimates of hedge funds' half-life to be exactly 30 months. Failure to account for survivorship bias can lead to an overstatement of hedge fund performance by 2 to 3% annually during the period before 2000 (Ackermann, McEnally, & Ravenscraft, 1999; Fung & Hsieh, 2000, 2002a; Liang, 2000) and much higher in more recent years (Aggarwal & Jorion, 2010a; Xu, Liu, & Loviscek, 2011). To address this issue, starting in 1994 TASS launched the 'Graveyard' database where all the funds which stopped reporting due to any reason were placed after they were removed from the 'Live' database. Therefore, in an effort to mitigate survivorship bias the dataset with individual funds begins from 1994 and includes funds both from the 'Live' and 'Graveyard' databases.

Instant history or backfilling bias arises because some funds backfill their historical returns when they first enter the database. Maintaining a profile with one of hedge fund databases is an effective way of pitching fund's services to prospective investors, because until recently hedge funds have been prohibited from marketing directly to US investors under the Investment Companies Act (1940)[48]. Therefore, funds have an incentive to bring their history to the database particularly if it is favourable. The practice of return backfilling is proven to create an upward bias in hedge fund performance analysis because only funds with superior historical performance opt to do so. The estimates of backfill bias vary substantially in the range from 1.4% (Fung & Hsieh, 2000) to 5% (Malkiel & Saha, 2005) annually. A common approach to reduce the instant history bias is to eliminate first 12-24

[48] See, www.sec.gov/about/laws/ica40.pdf. The ban has been lifted since September 2013, see, "Eliminating the Prohibition Against General Solicitation and General Advertising in Rule 506 and Rule 144A Offerings", Securities Act Release No. 33-9415 (July 10, 2013), available at http://www.sec.gov/rules/final/2013/33-9415.pdf

monthly performance observations (Ackermann et al., 1999; Fung & Hsieh, 2000; Kosowski et al., 2007). This adjustment, however, has some drawbacks. For funds with no backfill, the procedure discards several years of performance data, which are perfectly valid and very informative. For funds with backfill longer than 12-24 months, it still preserves the bias. Considering that the median backfill period in the entire TASS database is 480 days (4 years), as reported by Aggarwal and Jorion (2010b), the typical 1-2 year adjustment clearly may not be sufficient. An alternative and more straightforward way is to omit all the data prior to the date when a fund joined the database (Jagannathan, Malakhov, & Novikov, 2010). It is a safe approach to eliminate the instant history bias, though its cost is much smaller sample size. The TASS database allows identifying easily backfilled data, as it contains a field when the fund first joins the database[49]. Accordingly, in this study all the backfilled returns are truncated.

Another potential bias, which as instant history bias arises because of voluntary reporting, is self-selection bias. Public databases serve as an important information distribution channel for hedge funds, hence, fund managers with a poor track record are unlikely to disseminate their performance results and report to a data vendor. Also managers sometimes set up several funds and after incubation period select only the best performing one for public offer (Barry, 2002). Thus, hedge fund databases may provide a distorted picture of the true performance of the hedge fund universe, because they contain only a subset of funds with potentially superior performance. However, this upward performance bias is likely to be limited. As observed funds with good performance also drop from databases, for example, when they reach their target size and no longer wish to attract capital. Fung and Hsieh (2009)

[49] The field 'Date Added to TASS'

provide anecdotal evidence suggesting that out of 100 hedge fund firms from *Institutional Investor's* 2008 annual "Hedge Fund 100" survey, which is a list of the 100 largest hedge funds, 40% of the firms do not report to any of the four major databases (TASS, HFR, CISDM, Barclays). Similarly, 25% of all the firms ever listed in that survey have never reported performance to the mainstream public databases (Edelman, Fung, & Hsieh, 2013). Therefore, Fung et al. (2009) and Edelman et al. (2013) conclude that performance of the good funds missing from the databases would perhaps cancel out the missing performance of the bad funds, making the net effect of the selection bias negligible for practical purposes. On this ground in this study no specific correction is applied with regard to self-selection bias.

Another potentially serious problem concerning hedge fund data is return smoothing or stale price bias. In mathematical terms this bias implies serial correlation in hedge fund returns. The main reasons causing autocorrelation in returns is due to issues with pricing illiquid securities in hedge fund holdings. Hedge funds often trade illiquid securities such as distressed debt or emerging market bonds and equity. Whilst trading illiquid securities allows the hedge funds to earn a liquidity premium (Sadka, 2010), it introduces a serial correlation in hedge fund returns (Asness, Krail, & Liew, 2001), because lagged asset prices lead to delays in the reporting of returns. Stale price bias may have an important economic effect. Lo (2002) shows that it can reduce observed volatility of hedge fund returns and distort a funds' performance measures such as Sharpe ratios, information ratios and market betas. To mitigate the consequences of serial correlation, it is possible to unsmooth individual hedge fund returns. Getmansky, Lo and Makarov (2004) proposed an econometric methodology to reconstruct the original returns. This procedure is applied in this thesis. The details are given in Appendix III.

The last commonly accepted bias is multi-period sampling bias. In contrast to other biases it is not related to hedge fund databases or voluntary nature of reporting. Rather, it is induced by the research design of hedge fund studies. An empirical analysis of hedge fund's performance inevitably sets a requirement on the minimum length of fund's history. It is common to set 24 or 36 months constraint for a fund to be included in a research dataset (see, for example, Hasanhodzic and Lo (2007) and Diez de los Rios and Garcia (2011)). Fung and Hsieh (2000) estimate that the bias induced by such sample restriction is close to 0.6% p.a. given a 36-month history requirement and conclude that it is small enough to ignore it.

A nonparametric approach used in this study enforces a more stringent requirement on funds' history. It is recommended to have at least six to ten observations per each variable to accurately estimate nonparametric models (Wood, 2006). Accordingly for a model of six variables as in Hasanhodzic and Lo (2007) 60 observations are required. Furthermore, to analyse the persistence of the form of fund's exposure for RQ2.3 nonparametric model needs to be estimated twice in two non-overlapping periods (see Section 5.2.2). Thus, the requirement of minimum 120 observations for each fund has been imposed. Due to multi-sampling bias the results of the second research question should be interpreted with caution, bearing in mind that they are drawn from funds which survived relatively long period.

Besides the above mentioned biases there is evidence that fund managers engage in intentional manipulation and misreporting of returns. According to Bollen and Pool (2008) some managers attempt to delay reporting losses while fully reporting gains in order to improve end of the period performance results and increase incentive fees. As authors suggest the issue is particularly evident from an anomaly observed in the pooled distribution of hedge fund returns. Monthly return distribution exhibits a significant discontinuity around zero: the number of small gains far exceeds the number of small losses (Bollen & Pool, 2009). Reviewing plausible explanations of the anomaly Bollen and Pool (2009) suggest that the discontinuity is caused at least in part by temporarily overstated returns. Unfortunately, little can be done to identify and correct deliberately manipulated data, unless more stringent disclosure requirements are imposed on hedge funds.

To summarize, the procedures to correct for survivorship bias, instant history bias and return smoothing bias are applied to individual hedge fund data from the TASS database. All the results related to individual funds' analysis (in Chapter 7) are based on the data corrected for these biases.

4.3 HFR Data

As explained in Table 4.1 HFR indices are used along with TASS indices for the analysis of the third research question about the linear and nonlinear hedge fund replication. HFR indices are constructed from the hedge fund database maintained by Hedge Fund Research Inc. [50] Similar to the TASS database the HFR database has been extensively used in academic research[51,52]. HFR indices are calculated based on performance information reported voluntary by funds to the data provider. As of April 2014 the database comprised of over 7,500 funds and fund of funds[53].

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[50] The HFR indices are available at web-site of Hedge Fund Research Inc.: www.hedgefundresearch.com

[51] The HFR database is used, among others, by Liang (1999), Agarwal and Naik (2000a), Brunnermeier and Nagel (2004), Capocci and Hubner (2004), Teo (2009) Jagannathan, Malakhov, Novikov (2010), Frydenberg, Reiakvam, Thyness and Westgaard (2013), Harris and Mazibas (2013) and Lee and Kim (2014)

[52] For comparison of the TASS and the HFR databases see Liang (2000) and Fung and Hsieh (2002a)

[53]See https://www.hedgefundresearch.com/?fuse=database

There are several main reasons for using HFR indices along with TASS indices for the analysis of the third research question. Firstly, the purpose is to verify the results about hedge funds' nonlinear risk exposures on a new dataset. Since TASS indices are employed in the first part of this study (see Table 4.1) both for model selection and for examination of nonlinearities in hedge fund style portfolios there is a concern related to data snooping bias. Analysis of HFR indices in the third part of the thesis in addition to TASS indices mitigates this issue, because TASS and HFR databases differ substantially in terms of constituent funds and index construction methodology. The percentage of funds reporting to both databases does not exceed 22% as of December 2005 as estimated in Titman and Tiu (2011). Also, while TASS indices are value-weighted, HFR indices are equally-weighted.

Secondly, HFR maintains not only theoretical benchmarks of broad hedge fund universe, but also offers an investable version of its indices, as explained further. This is particularly important in light of the differences between the two types of indices discussed earlier in Section 3.2.3.

Finally, more recent history is available for HFR indices. While TASS indices are available from January 1994 to September 2010[54], HFR indices cover the period from January 1998 to February 2014. The post-crisis period (since 2009) is important, because the hedge fund industry has been rapidly evolving and a number of major regulatory changes have recently occurred. These changes in the regulatory environment could potentially affect the behaviour of hedge funds, their risk appetite and risk exposures[55].

[54] At the time this study was initiated the author had once-off access to the TASS database and the data were available only till September 2010. Recently Credit Suisse/TASS has made the data on TASS indices publicly available at www.hedgeindex.com

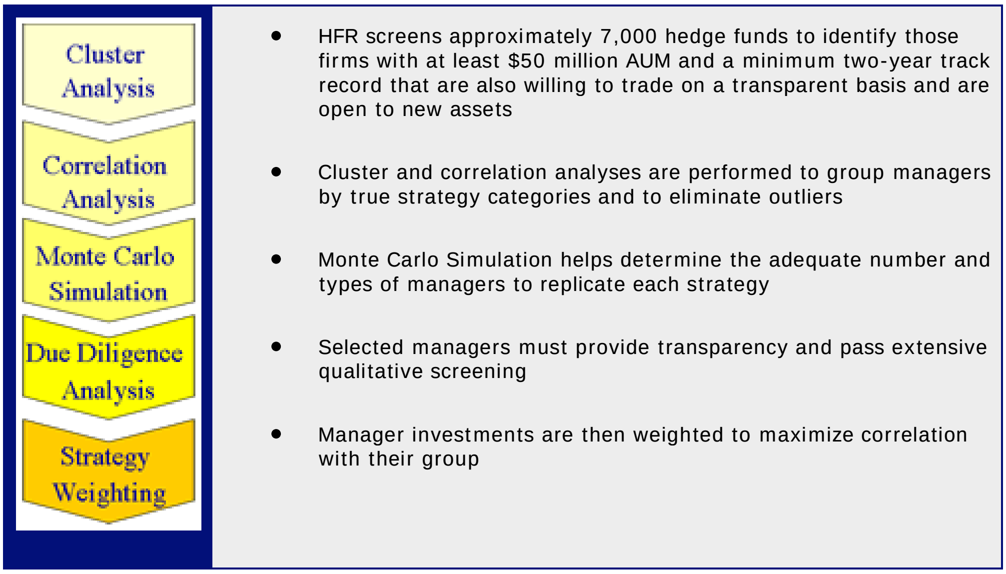
[55] The major change is related to the largest financial regulation overhaul since the 1930s – the Dodd–Frank Wall Street Reform and Consumer Protection Act (Pub.L. 111–203, H.R. 4173) and specifically to §619, the

HFR maintains three sets of hedge fund indices: HFRI, HFRX and HFRU. The HFRI indices are commonly considered in academic research and by industry professionals as broad hedge fund performance benchmarks. They are comprised of funds grouped by style satisfying minimum inclusion criteria (see criteria for fund inclusion below in Table 4.2). The HFRX indices are different to HFRI indices in that they are designed to be investable, offer full transparency and consistent fund selection (Markov & Wermers, 2013). Investors who are not willing to invest directly into hedge funds can opt to seek exposure to them through these investable hedge fund indices56. The selection criteria and the weighting scheme for the HFRX indices are a proprietary methodology developed by HFR. In short, HFR performs cluster and correlation analysis to group funds by their true style (because voluntary reported style attribute might not be representative of the fund's true strategy) and then executes an optimization process to select an optimal number of funds and assign weights in order to maximize correlation with their group. The procedure is outlined in Figure 4.1. HFRX indices according to their provider are one of the industry's most representative and fully investable strategy-based hedge fund indices (Boigner & Gadzinski, 2013).

Volcker rule. The Volcker rule prohibits US banks from engaging in proprietary trading that is not at the behest of its clients and from owning and investing in hedge funds.

[56] HFRX investable indices are available through tracker funds which are constructed by HFR Asset Management, LLC. Thus, the performance data on the HFRX indices used in this study are only 'a model output' and do not reflect the true performance of the investment vehicles. Also, the HFRX indices do not take into account the investment vehicle fees. For details, see www.hedgefundresearch.com/index.php?fuse=indices-faq&1397099730

Figure 4.1 HFRX Indices Methodology and Construction



Source: Hedge Fund Research

Lastly, the HFRU indices consist of a collection of UCITS (Undertakings for Collective Investment in Transferable Securities)[57] compliant hedge funds. UCITS compliant funds provide increased transparency through frequent disclosure of holdings, have limited leverage and attractive liquidity terms (Preqin, 2013). Since many of them are able to provide daily liquidity the HFRU indices are calculated on a daily basis. However, the history of HFRU indices is not long, since they were only launched in 2008. Table 4.2 summarizes the main characteristics of three sets of HFR indices.

[57] UCITS guidelines are as set of EU Directives that allow investment funds to distribute throughout the EU on the basis of a single authorization from one member state; UCITS is the latest iteration of this directive. Hedge funds structured under the UCITS wrapper are attractive to institutional investors for a number of reasons, including the increased transparency and disclosure of investments, limited leverage and attractive liquidity terms (Preqin, 2013).

Table 4.2 Characteristics of HFRI, HFRX and HFRU Indices

Category	HFRI Indices	HFRX Indices	HFRU Indices
Inception	Varies by index (Earliest 1990)	Varies by index (Earliest 1998)	Since 2008
Weighting	Equal-weighted	Varies by index (see explanation below)	Equal-weighted
Reporting Style	Net of all fees	Net of all fees	Net of all fees
Performance Time Series Available	Monthly	Daily or Monthly	Daily since 2011 Monthly since 2008
Index calculated	Three times per month	Daily and Monthly	Daily
Index performance finalized	Trailing four months of performance are subject to revision	Performance finalized at month-end	Trailing 5 days of performance are subject to revision
Index rebalanced	Monthly	Quarterly	Quarterly
Criteria for fund inclusion	Listing in HFR Database; Reports monthly net of all fees monthly performance and assets in USD	In addition to meeting HFRI criteria, fund must be open to new transparent investment and meet track record and minimum asset size requirements as listed below	Fund is UCITS compliant; Reports performance net of all fees at least bi-weekly
Minimum Asset Size and/or Track Record for fund inclusion	$50 Million minimum or > 12-Month Track Record	$50 Million and 24-Month Track Record (typical)	$10 Million EUR minimum or > 6-Month Track Record
Index Denomination	USD; some hedged to GBP, JPY, CHF & EUR	USD; some hedged to GBP, JPY, CHF & EUR	EUR; some hedged to GBP, JPY, CHF & USD
Investable Index	No	HFR Asset Management, LLC constructs investable products that track HFRX Indices	No
Constituents Details	Available to HFR Database subscribers	Available to HFR Database subscribers	Not available at this time
Number of Constituent Funds	Over 2200 in HFRI Fund Weighted Composite; over 500 in HFRI Fund of Funds Composite	Over 250 in total constituent universe, with over 60 of these in the HFRX Global Hedge Fund Index	Over 600 funds in the HFRU Hedge Fund Composite Index

Source: Hedge Fund Research

This study uses monthly data on non-investable HFRI indices and investable HFRX indices. The common time period for these indices spans from January 1998 to February 2014. Although a number of indices for specialized subcategories of hedge funds and funds with different geographical focus are available in the HFR database, following other studies (Giannikis & Vrontos, 2011) this study limits its scope to the indices corresponding to primary hedge fund strategies and several sub-strategies for which the match in HFRI and HFRX sets is possible. The selected categories and the mapping of HFRI and HFRX style names are presented in Table 4.3. The detailed description of strategies is given in Appendix II.

Table 4.3 Mapping of HFRI and HFRX Indices

Abbr.	Common Style Name	HFRI Index Name	HFRX Index Name
CA	Convertible Arbitrage	HFRI RV: Fixed Income-Convertible Arbitrage Index	HFRX RV: FI-Convertible Arbitrage Index
DS	Distressed/Restructuring	HFRI ED: Distressed/Restructuring Index	HFRX ED: Distressed Restructuring Index
ED	Event Driven	HFRI Event-Driven (Total) Index	HFRX Event Driven Index
EH	Equity Hedge	HFRI Equity Hedge (Total) Index	HFRX Equity Hedge Index
EMN	Equity Market Neutral	HFRI EH: Equity Market Neutral Index	HFRX EH: Equity Market Neutral Index
EW	Hedge Fund Composite	HFRI Fund Weighted Composite Index	HFRX Equal Weighted Strategies Index
M	Macro	HFRI Macro (Total) Index	HFRX Macro/CTA Index
MA	Merger Arbitrage	HFRI ED: Merger Arbitrage Index	HFRX ED: Merger Arbitrage Index
RVA	Relative Value	HFRI Relative Value (Total) Index	HFRX Relative Value Arbitrage Index

4.4 Risk Factors

Three previous sections describe the data on hedge fund indices as well as on individual hedge funds. Returns of indices and individual funds represent dependent variables in hedge fund pricing models. This section describes the proxies of systematic risk factors used as independent variables in the models.

There is a myriad of hedge fund strategies and they carry exposures to various aspects of systematic risk. Due to the lack of transparency of hedge funds the true set of priced risk factors is virtually unknown. Most of the earlier hedge fund studies derive the set of potential factors following the analysis of typical trading activities and strategies hedge funds engage in. Some of these strategies are explained in Section 3.1.1 and summarized in Table 3.1.

Table 4.4 lists some of hedge fund studies published during 1997-2013 and shows risk variables used therein. The table does not cover all hedge fund studies, because the volume of literature is very large; rather, it provides a broad overview of variables which have been used in hedge fund research. Some of these studies and variables have been briefly discussed in Chapter 3.

All variables in Table 4.4 are grouped into seven categories: equity, interest rates, credit, volatility, commodity, foreign exchange oriented variables and other variables. These groups correspond to the dominant types of risks a typical hedge fund is exposed to as identified earlier in Table 3.1[58].

A brief observation of the table is enough to realize that there is little consensus on what risk factors are priced and which proxies are appropriate. It is not surprising, given the diversity of hedge fund strategies. Number of variables used in hedge fund pricing models varies from one (Ackermann et al., 1999; Agarwal & Naik, 2000a; Brown, Goetzmann, & Ibbotson, 1999) to thirty one (Titman & Tiu, 2011). In practice, however, many studies, particularly those which employ more than six or seven factors, apply variable selection techniques. Variable selection procedures are very important in the context of hedge funds because they enable the identification of more parsimonious models.

Given the plethora of risks hedge funds are exposed to, a single-factor model is clearly inappropriate for hedge funds. Due to model misspecification, the alpha coefficient in a single factor hedge fund pricing model is therefore likely to be overstated. Capocci and Hubner (2004) test this conjecture empirically. The authors analyse hedge fund

[58] In Table 4.4 comparing with Table 3.1 the size and value spreads are included into equity category; liquidity risk is omitted as it has not been considered in the vast majority of studies, though it is found to be an important determinant in the cross-section of hedge-fund returns (Sadka, 2010).

performance using five different models: the CAPM, the three-factor model of Fama and French (1993); the international version of Fama and French's model which is comprised of two factors (Fama & French, 1998)[59]; the four-factor model of Carhart (1997); and a combined multi-factor model with eleven variables which include Fama and French's (1993) size and value factors, Fama and French (1998) international value factor, Carhart's (1997) momentum factor, a default factor (Lehman BAA Corporate Bond Index), a factor for non-US equities (MSCI World excluding US), three US and international bond factors (Lehman US Aggregate Bond Index, Salomon World Government Bond Index, and JP Morgan Emerging Market Bond Index), and a commodity factor (Goldman Sachs Commodity Index). While combined model explains 66% of return variation and has significant alpha of 0.25% monthly for all funds, the single-factor model has substantially lower R^2 coefficient of 44% and higher monthly alpha of 0.36%. These results confirm that multi-factor models should be preferred for hedge funds.

In general, the review of literature suggests that there are three sets of risk proxies which have gained popularity in academic research. These sets are the seven factors of Fung and Hsieh (2004b), the factors initially proposed by Agarwal and Naik (2004) and later modified by Vrontos, Vrontos, and Giamouridis (2008) into a set of thirteen variables, and the six factors of Hasanhodzic and Lo (2007). These sets of variables in Table 4.4 are highlighted in yellow, blue and green respectively.

The first set corresponds to the seven-factor Fung and Hsieh (2004b) model introduced in Section 3.1.3.1. It consists of the following factors: PTFS on bonds, PTFS on currencies, PTFS on commodities, equity market return, the size spread (difference between returns of small

[59] The data limitations did not allow Fama and French (1998) to thoroughly test size effect in international markets

and large companies), the change in the U.S. Federal Reserve 10-year constant maturity yield and the credit spread (difference between Moody's Baa yield and the Federal Reserve's 10-year constant maturity yield). The PTFSs are designed as rule-based strategies and reflect the return profile of trend-following funds from the Managed Futures category. It is worth mentioning that PTFSs variables are actually equal-weighted portfolios of PTFS on a number of underlying instruments: PTFS on bonds consists of PTFS in the U.S. 30-year Treasury bonds (CBOT), UK Gilts (LIFFE), German Bunds (LIFFE), the French 10-year Government Bond (MATIF), and the Australian 10-year Government Bond (SFE) futures and options markets; PTFS on currencies consists of PTFS in the British pound, Deutschemark, Japanese yen, and Swiss franc futures and options markets at the Chicago Mercantile Exchange (CME); and PTFS on commodities is comprised of PTFS in soybean, wheat, and corn futures and options markets at the Chicago Board of Traded exchange and gold, silver, and crude oil futures and options markets at the NYMEX. Also, in their original study on trend-following funds Fung and Hsieh (2001) had two other PTFSs on equities and short-term interest rates; however they were found to be insignificant in the regression models and thus omitted in the seven-factor model. Nevertheless, some studies (Bollen, 2013; Bollen & Pool, 2009) continue using PTFSs on equities and short-term interest rates apart from PTFS factors included in the seven-factor model.

Among asset based factors in the seven-factor Fung and Hsieh (2004b) model the yield change (T10Y) and the credit spread (CREDSPRD) capture the exposure of fixed income arbitrage strategies to interest rate risk, credit risk and liquidity. During times of market distress yield spreads tend to move together and can be modelled by the credit spread. Overall liquidity of the marketplace is also reflected in the credit spread variable. Equity market variable (SNPMRF) and the size spread (SCMLC) represent exposure to stocks of equity-oriented strategies and their tendency to be long the smaller-cap stocks and short the larger-cap stocks (Fung & Hsieh, 2004a).

An empirical test of the model demonstrates that the seven factors explain 55% of return variation of a typical hedge fund portfolio (proxied by the Fund of Funds index) and result in a statistically significant intercept term of approximately 48 bps per month (Fung & Hsieh, 2004b). The seven factors have been used in Kosowski et al. (2007), Fung et al. (2008), Ibbotson, Chen, and Zhu (2011) and Patton and Ramadorai (2013), among many others.

The second set of risk factors originally comes from the option-based factor model of Agarwal and Naik (2004) introduced in Section 3.1.3.2. It consists of sixteen variables[60] representing the U.S. equities (Russell 3000 index), world equities (Morgan Stanley Capital International (MSCI) world excluding the USA index), emerging markets equities (MSCI emerging markets index), size and value spreads (Fama & French, 1993), momentum factor (Carhart, 1997), the U.S. government and corporate bonds (Salomon Brothers government and corporate bond index), world bond market (Salomon Brothers world government bond index), high yield bonds (Lehman high yield index), default spread (the difference between the yield on the BAA-rated corporate bonds and the 10-year Treasury bonds), currencies (the U.S. Federal Reserve Bank competitiveness-weighted dollar index), commodities (the Goldman Sachs commodity index), as well as four option based factors (ATM call and put option on the S&P 500 index and OTM call and put option the S&P 500 index). Agarwal and Naik (2004) do not elaborate on the choice of buy-and-hold variables. To identify variables relevant for each strategy the authors use stepwise regression procedure. The results show

[60] Exclusive of the lagged value of equity variable in the original paper

that a majority of the hedge fund styles have significant exposure to equity (though it has a nonlinear pattern resembling payoff of short put option position), as well as an exposure to size and value spreads. Some other variables also appear to be important across different strategies.

Due to certain limitation and statistical problems related to estimation of option-based factors[61] the model of Agarwal and Naik (2004) has not been as widely accepted in the literature as the seven-factor Fung and Hsieh (2004b) model. Nevertheless, twelve buy-and-hold factors from this model have been used in a number of later studies (see, among others, Vrontos et al. (2008), Meligkotsidou, Vrontos, and Vrontos (2009), Giannikis and Vrontos (2011)). For instance, Giannikis and Vrontos (2011) augment these factors with a volatility factor (the change in equity implied volatility index) and employ them in a threshold regression model. They find each factor to be significant in at least one of the hedge fund categories. In contrast to stepwise regression used in Agarwal and Naik (2004) Giannikis and Vrontos (2011) rely on Bayesian approach and Markov Chain Monte Carlo methods to identify an optimal model.

Finally, the third set of factors is due to Hasanhodzic and Lo (2007). These factors are: the US Dollar Index return, the return on the Lehman Corporate AA Intermediate Bond Index, the spread between the Lehman BAA Corporate Bond Index and the Lehman Treasury Index, the S&P 500 total return; the Goldman Sachs Commodity Index total return, and the first-difference of the end-of-month value of the CBOE Volatility Index. As Hasanhodzic and Lo (2007) note these factors are appealing because, firstly, they provide a reasonably broad cross-section of risk exposures for a typical hedge fund (stocks, bonds, currencies,

[61] See Section 3.1.3.2

commodities, credit, and volatility), and, secondly, each of the factor returns can be realized through liquid financial instruments such as futures and ETFs. Indeed, the six factors correspond to the basic sources of the risks identified in Table 3.1. The ability to realize the returns of a model's factors through tradable instruments in the market is also important for investors. Fund managers often argue that they add value by providing access to some market niches that would otherwise be unavailable to investors. On this ground, academic models decomposing alpha and beta components of hedge fund returns, such as the seven-factor Fung and Hsieh (2004b) model, can be criticized because they include factors which are not easily accessible for investors (e.g. PTFS factors). Six factors of Hasanhodzic and Lo (2007) are free from this criticism. Moreover, Hasanhodzic and Lo (2007) develop the idea of portable beta[62] and in addition to performance evaluation of hedge funds demonstrate how the returns of hedge funds can be achieved through passive cloning of hedge fund strategies. The six factors of Hasanhodzic and Lo (2007) have been employed, among others, in Amenc et al. (2010) and Diez de los Rios and Garcia (2011).

[62] Portable beta refers to alternative beta strategies that can be easily implemented via available in the market financial assets and instruments

Table 4.4 Hedge Funds' Risk Factor Proxies

This table provides a summary of variables used in academic studies for modeling hedge fund returns. Highlighted in colours are the seven factors of Fung and Hsieh (2004); the thirteen factors of Vrontos et al. (2008) which are derived from factors of Agarwal and Naik (2004); and the six factors of Hasanhodzic and Lo (2007).

Study	Hedge Fund Category	Equity	Interest Rates	Credit	Volatility	Commodity	FX	Other	Total Factors	Notes
Fung and Hsieh (1997a)	• All funds	• MSCI US • MSCI Non-US • IFC EM	• JP Morgan US Gov. Bonds • JP Morgan non-US Gov. Bonds • 1M Euro-Dollar			• Gold	• FRB US Dollar		8	
Fung and Hsieh (1997b)	• CTA	Same as in Fung and Hsieh (1997a)						• Merrill Lynch High Yield Bonds	9	
Ackermann et al. (1999)	• 8 MAR strategies[1]	• S&P 500							1	CAPM for US market
		• MSCI EAFE							1	CAPM for developed markets outside US
Liang (1999)	• 16 HFR strategies[2]	Same as in Fung and Hsieh (1997a)							8	
Fung and Hsieh (2001)	• Trend-following	• S&P 500 • FTSE 100 • DAX 30 • Nikkei 225 • Australian All Ordinaries	• US 30Y • UK Gilt • German Bund • French 10Y • Australian 10Y • 3M Euro-Dollar • 3M Sterling • Euro-DM • Euro-Yen • Australia Bankers Acceptance • Paris Interbank			• Corn • Wheat • Soybean • Crude Oil • Gold • Silver	• British Pound • Deutsche Mark • Japanese Yen • Swiss Franc		26	Primitive Trend Following Strategies (PTFS) on underlying variables
Fung and Hsieh (2004b)	• All funds • Fund of Funds	• S&P 500 • Wilshire Small Cap 1750 - Wilshire	• Yield change of 10Y T-bond	• Spread between Moody's Baa and 10Y Treasury				• PTFSBD • PTFSFX • PTFSCOM	7	7-factor Fung-Hsieh model

		Large Cap 750								
Agarwal and Naik (2004)	• Event Arbitrage • Restructuring • Event Driven • Relative Value • Convertible Arbitrage • Equity Hedge • Equity Non-hedge • Short Selling	• Russell 3000 • MSCI Non-US • MSCI EM • SMB • HLM • UMD	• Salomon Gov. and Corp. Bonds • Salomon World Gov. Bonds	• Spread between Moody's Baa and 10Y Treasury		• Goldman Sachs Commodity Index	• FRB US Dollar	• Lehman High Yield Bonds • ATM S&P 500 call • ATM S&P 500 put • OTM S&P 500 call • OTM S&P 500 put	16	
Capocci and Hubner (2004)	• 16 HFR and 23 MAR strategies[3]	• Market - value-weighted portfolio of all NYSE, Amex and Nasdaq stocks	• 1M T-Bill rate						1	CAPM
		• Market • SMB • HML	• 1M T-Bill rate						3	Fama and French (1993) model
		• Market • IHML	• 1M T-Bill rate						2	International Fama and French (1998) model
		• Market • SMB • HML • UMD	• 1M T-Bill rate						4	Carhart (1997) model
		• Market • SMB • HML • IHML • UMD • MSCI Non-US	• 1M T-Bill rate • Lehman US Aggregate Bond • Lehman BAA Corp. Bond • Salomon World Government Bond • JP Morgan Emerging Market Bond			• Goldman Sachs Commodity Index			11	

Jaeger and Wagner (2005)	• 11 HFR strategies[4]	• S&P 500 • Russell 2000 • MSCI EM	• MSCI US Treasury		• VIX			• Credit Suisse High Yield Bonds	6	
		• S&P 500 • Russell 3000 Value • Small-Cap Spread (Wilshire) • Value Spread (MSCI) • UMD • MSCI EM	• MSCI US Treasury • Citigroup WGBI • JP Morgan EM Global Bonds			• Goldman Sachs Commodity Index		• Citigroup Convertible • Citigroup Convertible Inv. Grade • CSFB High Yield • BXM Covered Call Writing • sGFI Futures Index	Not known	All factors used for variable selection are not reported
Hasanhodzic and Lo (2007)	• 11 TASS strategies[5]	• S&P 500	• Lehman Corp. AA Intermediate Bond	• Spread between Lehman BAA and Treasury	• DVIX	• Goldman Sachs Commodity Index	• FRB US Dollar		6	6-factor Hasanhodzic-Lo model
Kosowski et al. (2007)	• Individual funds from TASS, HFR, CISDM and MSCI	Same as in Fung and Hsieh (2004b)							7	
Fung et al. (2008)	• Fund of Funds	Same as in Fung and Hsieh (2004b)							7	
Vrontos et al. (2008)	• TASS Aggregate • Long-Short Equity	• Russell 3000 • MSCI Non-US • MSCI EM • SMB • HLM • UMD	• Salomon Gov. and Corp. Bonds • Salomon World Gov.	• Spread between Moody's Baa and 10Y Treasury	• DVIX	• Goldman Sachs Commodity Index	• FRB US Dollar	• Barclays HY Bonds	13	Same as in Agarwal and Naik (2004), but excludes four option factors and includes a volatility factor
Meligkotsidou et al. (2009)	• 13 HFR strategies[6]	Same as in Vrontos et al. (2008)							13	
Bollen and Whaley (2009)	• All CISDM Funds • CTA • CPO • Fund of Funds	• F-F Market • SMB • HML • SMB Squared • HML Squared	• Yield change of 10Y T-bond	• Spread between Moody's Baa and 10Y Treasury				• PTFSBD • PTFSFX • PTFSCOM • PTFSIR • PTFSSTK	12	
		• S&P 500	• Euro-Dollar • T-bond			• Light Crude Oil • Natural Gas • Corn	• Canadian Dollar • Japanese Yen		10	All factors are returns on futures cotracts

						• Gold	• Swiss Franc			
Amenc et al. (2010)	• 12 TASS strategies[7]	• S&P 500 • S&P 600 Small Cap minus S&P 500 • IFC EM	• Lehman Corp. AA Intermediate Bond	• Spread between Lehman BAA and Treasury • Spread between Lehman BAA and AAA		• GSCI	• FRB US Dollar	• Merrill Lynch 300 Global Convertible Bonds • Mortgage spread: GNMA minus Lehman US T-Bill	10	
		Same as in Hasanhodzic and Lo (2007), excluding DVIX							5	
Giamouridis and Paterlini (2010)	• Equity Hedge • Event Driven • Macro • Relative Value	• S&P 500 • Russell 2000 • Russell 2000 Total Return • DJIA • MSCI World • MSCI EAFE • MSCI EM • Bovespa Brazil • Hang Seng	• Citigroup Treasury • Citigroup World Gov. 1-3Y • Citigroup World Gov. 7-10Y • Broad Investment-Grade Bond • Cash		• VIX	• GSCI • Gold • Crude Oil	• FRB US Dollar	• FTSE EPRA/NAREIT Global Real Estate	20	
Ibbotson et al. (2011)	• 9 TASS strategies[8]	• S&P 500	• US Intermediate Term T-Bond • US T-Bill						6	Authors also include lagged returns
		Same as in Fung and Hsieh (2004b)							7	
Giannikis and Vrontos (2011)	• 13 HFR strategies[9]	Same as in Vrontos et al. (2008)							13	
Diez de los Rios and Garcia (2011)	• 10 TASS strategies[10]	Same as in Hasanhodzic and Lo (2007), excluding DVIX							5	
Titman and Tiu (2011)	• 8,500 individual funds from TASS, HFR, mHedge, HedgeFund.net and Altvest	• Russell 3000 • NASDAQ • SMB • HML • UMD • FTSE 100 • Nikkei 225 • MSCI EAFE • MSCI EMF • DAX 30	• Barclays Aggregate Bond Index • Salomon Borthers five-year Index of Treasuries • Barclays Index of ten-year municipal bonds	• Default Spread • Duration Spread		• GSCI • Average of three oil price indices • Gold price changes	• Salomon Brothers Non-US Unhedged Dollar Index	• NAREIT US Real Estate • Barclays Aggregate of MBS • PTFSBD • PTFSFX • PTFSCOM • PTFSSTK • ITM S&P 500	31	

		• CAC 40	• Salomon Brothers Non-US Weighted Government with 5-7 year duration					call • ITM S&P 500 put • OTM S&P 500 call • OTM S&P 500 put		
Patton and Ramadorai (2013)	• 10 strategies from TASS, HFR, CISDM, Morningstar and BarclayHedge[11]	Same as in Fung and Hsieh (2004b)							7	

[1] Event Driven, Fund of Funds, Global, Global Macro, Market Neutral, Short Sales, U.S. Opportunistic, Total;

[2] Composite, Convertible Arbitrage, Distressed securities, Emerging market, Fixed Income, Foreign Exchange, Fund of Funds, Growth, Macro, Market Neutral, Market Timing, Merger Arbitrage, Opportunistic, Sector, Short Selling, Value;

[3] Event Driven (Distressed Securities, Risk Arbitrage and Non Sub-strategy); Global (International, Emerging, Regional Established); Global Macro; Market Neutral (Long/Short, Convertible Arbitrage, Fixed Income, Stock Arbitrage, Mortgage-Backed Securities, Relative Value Arbitrage); Short Sellers; US Opportunistic (Growth, Value, Small Caps); Long only Leveraged; Market Timing; Equity non-Hedge; Foreign Exchange; Sector; Fund of Funds; Not Classified; All funds;

[4] Equity Hedge, Equity Market Neutral, Short Selling, Event Driven, Distressed, Merger Arbitrage, Fixed Income Arbitrage, Convertible Arbitrage, Macro, Managed Futures, Managed Futures Trend Following;

[5] Convertible arbitrage, Dedicated Short Bias, Emerging Markets, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Global Macro, Long-Short Equity, Managed Futures, Multi-Strategy, Fund of Funds;

[6] Convertible Arbitrage, Distressed Securities, Event Driven, Equity Hedge, Equity Market Neutral, Fixed Income Arbitrage, Macro, Merger Arbitrage, Market Timing, Relative Value Arbitrage, Emerging Markets Total, Equity Non-Hedge, Short Selling;

[7] Convertible Arbitrage, Managed Futures, Distressed Securities, Emerging Markets, Equity Market Neutral, Event Driven, Fixed-Income Arbitrage, Global Macro, Long-Short Equity, Risk Arbitrage, Dedicated Short Bias, Fund of Funds;

[8] Convertible Arbitrage, Emerging Markets, Equity Market Neutral, Event Driven, Fixed Income, Global Macro, Long-Short Equity, Managed Futures;

[9] Equity Hedge, Macro, Relative Value, Event Driven, Merger Arbitrage, Equity Market Neutral, Fixed Income-Corporate, Short Bias, Emerging Markets, Fixed Income-Convertible Arbitrage, Multi-Strategy, Distressed/Restructuring, Quantitative Directional;

[10] Convertible Arbitrage, Fixed Income Arbitrage, Event Driven, Equity Market Neutral, Long–Short Equity, Global Macro, Emerging Markets, Dedicated Short Bias, Managed Futures, Funds of Funds, Emerging Markets;

[11] Security Selection, Global Macro, Relative Value, Directional Traders, Funds of Funds, MultiProcess, Emerging Markets, Fixed Income, CTAs, and Other.

Following the discussion of the literature, this thesis utilizes the seven factors of Fung and Hsieh (2004b) (FH7), the six factors of Hasanhodzic and Lo (2007) (HL6) and slightly modified set of fourteen variables which extends thirteen factors of Vrontos et al. (2008) (14 factors, thereafter). In Vrontos et al. (2008) six variables are analogous to HL6 variables. Thus, among 14 variables in the extended set, six variables are due to Hasanhodzic and Lo (2007), an additional seven are from Vrontos et al. (2008) and the remaining variable, for convertible bonds, is due to Agarwal, Fung, et al. (2011). Table 4.5 lists all the variables and associated data sources. As explained further in Chapter 5, these three factor sets are used independently: the linear model with FH7 factors is compared against the linear model with HL6 factors and a number of nonparametrically estimated models with HL6 variables and the extended set of 14 factors.

In the 14-factor set, the additional eight variables (besides HL6 factors) are: Fama and French's (1993) size (SMB) and book-to-market factors (HML), Carhart's (1997) momentum factor (UMD), the Morgan Stanley Capital International (MSCI) World excluding US index (EQINT), the MSCI Emerging Markets index (EQEM), the Barclays US Corp High Yield Total Return index (HYIELD), the Citigroup World Government Bond Total Return index (BONDINT) and the BofA Merrill Lynch All US Convertibles Total Return index (BONDCNV). Five of these variables are equity related (SMB, HML, UMD, EQINT, EQEM) and three are credit and interest rate related (HYIELD, BONDINT, BONDCNV). Size and value spreads are fundamental sources of risk for equity oriented and equity-market neutral hedge fund strategies as explained in Section 3.1.1. It is considered that they represent macroeconomic risk factors capable of explaining asset returns (Liew & Vassalou, 2000) as well as hedge fund returns (see, among others, Capocci and Hubner (2004), Fung and Hsieh (2004b), Agarwal and Naik

(2004), Fung et al. (2008)). Theoretical and empirical evidence supporting the importance of Carhart's (1997) momentum factor in hedge funds is weaker[63]; nevertheless it is included into the extended set because Carhart's (1997) four-factor model is widely used in asset pricing. International and emerging equity market variables are included to account for exposure to world equity markets in many hedge fund categories such as the Global Macro, the Emerging Markets and the Managed Futures styles. As documented in the literature returns of emerging markets funds are highly correlated with the broad emerging markets equity index[64]: the correlation coefficient of 0.78 is reported in Lhabitant (2006, p. 324)[65]. The inclusion of the convertible bonds variable is motivated by the studies of Fung and Hsieh (2002b), Agarwal, Fung, et al. (2011) and Brown, Grundy, Lewis, and Verwijmeren (2012) on convertible arbitrage funds[66]. These studies show that returns of a buy-and-hedge strategy alone, i.e. taking a long position in convertible bonds while hedging the equity risk, explains a substantial amount of these funds' return dynamics. Hence, a combination of convertible bond variable and an equity risk variable is supposed to provide a good proxy for the behaviour of convertible arbitrage funds. Finally, the high yield bond variable should capture the exposure of funds from several categories such as the Fixed Income Arbitrage and the Distressed Securities strategy of the Event Driven style to default risk and liquidity risk associated with investments in non-investment grade bonds.

[63] Capocci and Hubner (2004) analyses performance of hedge fund strategies and finds that the momentum factor does not prove to be a strong indicator of hedge funds behaviour

[64] This thesis uses MSCI Emerging Markets Index. As of 2014 it covers over 800 securities across 23 markets and represents approximately 11% of world market cap (http://www.msci.com/products/indexes/country_and_regional/em/)

[65] This estimate is in line with the figure calculated in this thesis of 0.8 reported further in Section 6.1

[66] Fung and Hsieh (2002b) examine funds from the Fixed Income category of the HFR database. Convertible Arbitrage strategy there is a sub-category of the Fixed Income category.

Table 4.5 Description of Variables

The table contains the details on sources of data on variables used in hedge fund pricing models. The variables are grouped into three categories: the seven factors of Fung and Hsieh (2004b); the six factors of Hasanhodzic and Lo (2007) and additional eight factors (exclusive of risk-free rate) as identified from the literature. Unless otherwise specified, the default data source is DataStream and the last column contains the DataStream ticker.

Variable name	Description	Risk Dimension	Source
	FH7 Factors		
SNPMRF	The Excess return on the S&P 500 Total Return Index	Market Risk	S&PCOMP(RI)
SCMLC	The Russell 2000 Total Return Index minus the S&P 500 Total Return Index	Size Spread	FRUSS2L(RI), S&PCOMP(RI)
T10Y	The monthly change in the 10-year treasury constant maturity yield (month end-to-month end)	Interest Rate Risk	FRS web-site[67]
CREDSPR	The change in the credit spread of Moody's BAA bond over the 10-year Treasury bond	Credit Risk	FRS web-site
PTFSBD	Bond Trend-Following Factor	PTFS on Bonds	David A. Hsieh's Data Library[68]
PTFSFX	Currency Trend-Following Factor	PTFS on Currency	David A. Hsieh's Data Library
PTFSCOM	Commodity Trend-Following Factor	PTFS on Commodities	David A. Hsieh's Data Library
	HL6 Factors		
SP500	The S&P 500 Total Return Index	Market Risk	S&PCOMP(RI)
USD	ICE FINEX Dollar Index Futures Return	Currency Risk	NDXCS00(PS)
BOND	Barclays US Aggregate Corporate AA Intermediate Bond Total Return Index	Interest Rate Risk	LHIGAAI(TOTR)
CREDIT	The spread between the Barclays US Aggregate Corporate AA Total Return Index and Barclays US Treasury Total Return Index	Credit Risk	LHIGBAA(TOTR), LHUSTRY(TOTR)
GSCI	Goldman Sachs Commodity Total Return Index	Commodity Risk	GSCITOT(TR)
DVIX	The first difference of the end-of-month value of the CBOE Volatility Index	Volatility Risk	CBOEVIX(PI)
	Additional Factors		
SMB	Fama and French Size Factor	Size Spread	Kenneth R. French Web-Site[69]
HML	Fama and French Book to Market Factor	Value Spread	Kenneth R. French Web-Site
UMD	Carhart's Momentum Factor	Momentum	Kenneth R. French Web-Site
EQINT	The Morgan Stanley Capital International World excluding US Return Index	International Market Risk	MSWRLD$(RI)
EQEM	The Morgan Stanley Capital International Emerging Markets Return Index	Emerging Markets Market Risk	MSEMKF$(RI)
HYIELD	The Barclays US Corp High Yield Total Return Index	Default Risk	LHYIELD(TOTR)
BONDINT	The Citigroup World Government Bond Total Return Index	International Interest Rate Risk	SBNUUII(RI)
BONDCNV	The BofA Merrill Lynch All US Convertibles Total Return Index	Buy-and-Hold Convertible Bond Strategy	MLCVXA0(RI)
RF	3-Month US Treasury Bill Rate	Risk-Free Rate	USGBILL3

[67] http://www.federalreserve.gov/releases/h15/data.htm

[68] https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm

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

Chapter 5 Methodology

This chapter explains research methodology employed for investigation of three research questions formulated in Chapter 3. These research questions focus on (1) modeling and examination of nonlinearities in hedge fund portfolios; (2) examination and assessment of nonlinearities in individual funds; and (3) application of linear and nonlinear hedge fund pricing approaches to hedge fund replication.

A significant part of this chapter is devoted to developing models of hedge fund risk and return. Particularly, the focus is on nonparametric approaches, since examination of nonlinear features is the central idea of this thesis. The structure of the chapter is as follows. Section 5.1 introduces and described all the models. It also presents statistical tests used to address the first research question. Section 5.2 deals with methodology for investigation of the second research question. Section 5.3 explains how to apply linear and nonparametric models for hedge fund replication; it also formulates statistical tests associated with the third research question.

5.1 Hedge Fund Pricing Models

As the aim of this thesis is to examine hedge funds' nonlinear risk exposures, it is essential to develop an appropriate statistical methodology for modeling nonlinearities. To this end this section introduces a number of models, discusses the rationale behind each model, and presents statistical tests that are used to evaluate and compare the models.

There are two main requirements that guide the choice of an appropriate statistical model of hedge fund risks and returns. First, since risk exposures may have a nonlinear form, the model should allow the capture of nonlinear effects. Second, due to the plethora of risk factors that hedge funds are potentially exposed to (see Table 3.1 and Table 4.4), it should encourage the selection of a parsimonious set of risk factors. In statistical terms these requirements mean that the model should be sufficiently flexible to accommodate nonlinearities in the data, and perform variable selection so as to find an optimal set of risk factor proxies for each hedge fund style.

These requirements naturally suggest that nonparametric statistical learning techniques could be quite efficient and useful in the context of hedge funds. Statistical learning techniques are employed in tasks with little a priori knowledge about the data generating process, but when serious reasons exist to suspect that the relationship between response and predictor variables can be more complex than linear. According to Berk (2008, p. 8) "statistical learning is likely to shine when the functional forms are unknown and substantially nonlinear". Another advantage of nonparametric learning techniques is related to powerful variable selection techniques which are often either embedded into or can be easily used in conjunction with model fitting procedures. Given the theoretical arguments about potentially nonlinear risk-return relationship in hedge funds as well as empirical evidence in the literature (see Section 3.1), nonparametric methods seem to be a reasonable alternative to existing linear regression methods.

A number of nonparametric techniques are available for a data analyst today. They include artificial neural networks (Ripley, 1993; White, 1992), projection pursuit (Friedman & Stuetzle, 1981), alternating conditional expectations (Breiman & Friedman, 1985), recursive partitioning (Breiman, Friedman, Olshen, & Stone, 1984) and other methods. The main focus in this thesis is on a technique known as a Generalized Additive Model (Hastie & Tibshirani, 1990). In short a GAM is a flexible data-driven technique which preserves the additive form of regression models. This specific choice from the large collection of nonparametric techniques requires some explanation and justification.

Most of the nonparametric techniques are traditionally criticized as sacrificing ease of interpretation for the accuracy of fit (Beck & Jackman, 1998). For instance, projection pursuit method is designed to find orthogonal projections through the space of the data that maximize model fit; however, interpretation of projections is complicated. Alternating conditional expectations (ACE) method finds optimal transformations of response and predictor variables that also maximize fit to the model, but again, the resulting fit might be hard to interpret.

In contrast to these methods, GAMs provide a sensible compromise between the ease of interpretation and flexibility. On the one hand, GAMs have flexibility of nonparametric methods, because functional form of a GAM is guided by the data. On the other hand, GAMs are similar to linear regression models in that they have additive structure. The additive property means that the effect of each of independent variable on response variable can be treated separately. In other words nonlinear effects can be analysed and assessed variable by variable. Also, additive property of GAMs means that they can be effectively compared with linear regression models and statistical tests can be performed to evaluate the importance of individual nonlinear effects and check validity of the model as a whole. To summarize, GAMs are a relatively small step away from a linear regression, compared with other nonparametric techniques such as artificial neural networks. They provide much of the flexibility of nonparametric methods, and at the same time are more transparent.

GAMs are not new to statistics. They have been used in statistical analysis for more than two decades. During this time, the underlying theory on estimation and inference in GAMs has been developed and extensively tested[70]. GAMs have found many applications in finance including modelling bankruptcy prediction (Berg, 2007), analysis of sustainability of the US public debt (Greiner & Kauermann, 2007), analysis of determinants of hedge fund returns and hedge fund failure (Lahiri et al., 2013; Tupitsyn & Lajbcygier, 2013) and real estate appraisal (Pace, 1998). Applications in other field are numerous[71].

Similar to various fitting methods which exist for estimation of a linear regression model, a number of ways exist to fit a GAM. They differ in terms of underlying smoothing functions, estimation methods and associated variable selection procedures. Three versions of GAMs are considered in the thesis: GAMs using loess smoothers, GAMs using cubic splines smoothers and GAMs using a component-wise gradient boosting approach. GAMs using loess are discussed in Section 5.1.2.1. GAMs using splines are presented in Section 5.1.2.2. GAMs via gradient boosting are described in Section 5.1.3. The latter approach permits fitting a robust version of a GAM. While a standard version of a GAM typically makes the same assumption of normality for the residual distribution as in a linear model, the component-wise gradient boosted GAM allows more easily for the inclusion of other distributions and loss functions that are less sensitive to the presence of outliers in the data.

[70] See excellent books on GAMs by Hastie and Tibshirani (1990) and Wood (2006)

[71] Some examples of application of GAMs beyondfinance include: Guisan and Hastie (2002), Leathwick, Elith and Hastie (2006), Yee and Mitchell (1991) in ecology; Dominici, McDermott, Zeger and Samet (2002), Hastie and Tibshirani (1995), Ramsay, Burnett and Krewski (2003) in medicine.

This is another advantage of the GAM technique, particularly important in the hedge fund context.

With GAMs being the main focus of the thesis, there are several benchmark methods against which GAMs are evaluated. The first natural benchmark is a linear regression model and its modification with variable selection procedure, a stepwise linear regression model. The second benchmark is a robust version of a linear regression model, a median regression (a specific version of a quantile regression (Koenker & Bassett, 1978)). A median (quantile) regression is suited well for residual distributions characterised by large skewness, kurtosis, and fat tails, or which in general deviate from normality (Buchinsky, 1998; Meligkotsidou et al., 2009). A median regression can be fitted using the same procedure as a robust version of a GAM. Finally, the last proposed benchmark is a multivariate adaptive regression spline (MARS) of the first degree. Essentially, a first degree MARS represent a piecewise linear regression function. A number of studies model hedge fund returns with piecewise linear functions, though not with MARS (Agarwal & Naik, 2004; Diez de los Rios & Garcia, 2011; Giannikis & Vrontos, 2011). A piecewise linear regression can be considered as an interim model between completely smooth (i.e. straight line) linear regression model and flexible nonparametric techniques such as GAMs. Therefore, it is interesting to test whether GAMs provide any additional benefit over a piecewise linear regression approach.

The hierarchy of the models examined in the thesis as well as their main features are given below:

Figure 5.1 Hierarchy of Models

Linear Regression
- Additive structure, easy to interpret

Stepwise Linear Regression
- Additive structure, easy to interpret
- Automatic variable selection

Robust Linear Regression
- Additive structure, easy to interpret
- Automatic variable selection
- Robust to deviations from normality and outliers

Multivariate Adaptive Regression Splines
- Additive structure
- Automatic variable selection
- Semiparametric (piecewise linear)

Generalized Additive Model
- Additive structure
- Automatic variable selection
- Flexibility of fit

Robust Generalized Additive Model
- Additive structure
- Automatic variable selection
- Flexibility of fit
- Robust to deviations from normality and outliers

It is necessary to note that implementation of each feature specified in this hierarchy is specific to the model. For instance, implementation of the variable selection procedure is different in standard GAM, robust GAM, MARS and a stepwise linear regression model.

All the models used in this thesis and their main characteristics are summarized in Table 5.1. Following sections discuss in detail each model.

Table 5.1 Description of Models

Model	Type	Base Smoother	Fitting Procedure	Variables	Main Parameters	Automatic Variable Selection
			Linear Models			
FH7	Linear regression	N/A	Ordinary Least Squares	FH7 factors	N/A	No
HL6	Linear regression	N/A	Ordinary Least Squares	HL6 factors	N/A	No
SLM14	Stepwise Linear Regression	N/A	Ordinary Least Squares	14 factors	AIC variable selection	Yes
RLM6	Robust Linear Model (Median Reg.)	N/A	Component-Wise Gradient Boosting	HL6 factors	Absolute loss; 25-fold bootstrap cross-validation	Yes
RLM14	Robust Linear Model (Median Reg.)	N/A	Component-Wise Gradient Boosting	14 factors	Absolute loss; 25-fold bootstrap cross-validation	Yes
			Nonparametric Models			
GAML6	Generalized Additive Model	Loess	Backfitting Algorithm	HL6 factors	Bandwidth = 1	No
SGAML14	Stepwise Generalized Additive Model	Loess	Backfitting Algorithm	14 factors	Bandwidth = 1	Yes
GAMS6	Generalized Additive Model	Cubic spline	Penalized Likelihood Maximization	HL6 factors	Maximum degrees of freedom = 6	No
GAMS14	Generalized Additive Model	Cubic spline	Penalized Likelihood Maximization	14 factors	Maximum degrees of freedom = 6	Yes
RGAMS6	Robust Generalized Additive Model	Cubic spline	Component-Wise Gradient Boosting	HL6 factors	Absolute loss; 25-fold bootstrap cross-validation	Yes
RGAMS14	Robust Generalized Additive Model	Cubic spline	Component-Wise Gradient Boosting	14 factors	Absolute loss; 25-fold bootstrap cross-validation	Yes
MARS6	Multivariate Adaptive Regression Splines	Regression spline	Forward and Backward Pass	HL6 factors	Order of polynomials is 1	Yes
MARS14	Multivariate Adaptive Regression Splines	Regression spline	Forward and Backward Pass	14 factors	Order of polynomials is 1	Yes

5.1.1 Linear Regression Models

Since Sharpe's (1992) original idea to use multiple linear regression framework for style analysis of mutual funds, numerous studies have applied a multi-factor linear regression for modelling hedge fund returns. A multi-factor hedge pricing model postulates a linear relationship between hedge fund style returns (or individual fund returns) and a set of risk factors:

$$R_{i,t} = \alpha_i + \sum_{j=1}^{N} \beta_{i,j} F_{j,t} + \varepsilon_{i,t} \tag{5.1}$$

where $R_{i,t}$ is the return of a hedge fund style portfolio i at time t in excess of the risk-free rate, $i = 1,..,M$; α_i is an abnormal return; $F_{j,t}$ – excess return on factor F_j at time t, $j = 1, \dots, N$; $\varepsilon_{i,t}$ is the residual return of style i at time t, such that $\varepsilon_{i,t} \sim N(0, \sigma_i^2)$. The linear form of the relationship (5.1), normality of the error term distribution and the predetermined set of factors used to explain hedge fund returns are the key assumptions of a multi-factor model. The first two assumptions of linearity and normality are rarely backed up theoretically in the hedge fund literature and are inherited from traditional asset pricing models such as the CAPM and the APT.

In terms of the set of risk factors there are many different views, as explained in details in Section 4.4. Fung and Hsieh (2004b) advocate for the following variables to be included into model (5.1) (FH7 variables, thereafter): US equity market return (SNPMRF); size premium of small stocks over large stocks (SCMLC); change of long-term interest rate (T10Y), credit spread (CREDSPRD); and returns on three primitive trend-following strategies in bond market (PTFSBD), currency market (PTFSFX) and commodity market (PTFSCOM).

Hasanhodzic and Lo propose to include into model (5.1) another six variables, which are supposed to cover a reasonably broad cross-section of risk exposures for a typical hedge fund (HL6 variables, thereafter): US equity returns (SP500); US currency rate relative to the basket of major global currencies as determines by the Federal Reserve's US Dollar Index (USD); US bond market returns (BOND); credit spread (CREDIT); commodity market returns (GSCI); and US equity market volatility (DVIX). The definitions of these variables are given in Chapter 5 Data, table 5.1.

Linear models based on FH7 and HL6 factors are formulated as follows:

Model FH7

$$\begin{aligned} R_{i,t} = \quad & \alpha_i + \beta_{i,1} SNPMRF + \beta_{i,2} SCMLC + \beta_{i,3} T10Y + \beta_{i,4} CREDSPRD \\ & + \beta_{i,5} PTFSBD + \beta_{i,6} PTFSFX + \beta_{i,7} PTFSCOM + \varepsilon_{i,t} \end{aligned} \tag{5.2}$$

Model HL6

$$\begin{aligned} R_{i,t} = \quad & \alpha_i + \beta_{i,1} SP500 + \beta_{i,2} USD + \beta_{i,3} BOND + \beta_{i,4} CREDIT \\ & + \beta_{i,5} GSCI + \beta_{i,6} DVIX + \varepsilon_{i,t} \end{aligned} \tag{5.3}$$

These two linear models are used as benchmarks for other more complex models. They have been widely used in academic literature. Model FH7 has been used in Kosowski et al. (2007), Meligkotsidou and Vrontos (2008), Bollen and Whaley (2009), Teo (2009), Agarwal, Daniel, and Naik (2011), Olmo and Sanso-Navarro (2012), and Patton and Ramadorai (2013), among others. Model HL6 has been applied in Amenc et al. (2010) and Tancar, Poddig, and Ballis-Papanastasiou (2012) among others. While model FH7 is considered to be theoretically driven, at least to some extent (see Section 3.1.3.1), model HL6 is more oriented to practical applications due to availability of market proxies for all its variables.

As explained in section 4.4 this thesis employs another eight additional variables identified as important risk factor proxies in earlier studies: Fama and French (1992, 1993) size (SMB) and value (HML) factors; Carhart's (1997) momentum factor (UMD); world equity returns (EQINT); emerging markets equity returns (EQEM); world bond market returns (BONDINT); high yield bonds returns (LHYIELD); and convertible bonds returns (BONDCNV) (see, among others, Capocci and Hubner (2004), Vrontos et al. (2008), Amenc et al. (2010), Giannikis and Vrontos (2011)).

Since factors relevant to pricing each hedge fund style are likely to vary, a common approach to select a parsimonious model is to use a stepwise regression procedure. Stepwise variable selection procedure has been used in Liang (1999), Agarwal and Naik (2000b), Agarwal and Naik (2004), Titman and Tiu (2011), Darolles and Vaissié (2012), among many others. The procedure involves adding and/or deleting variables sequentially to the model and comparing candidate models either by means of a statistical test (e.g. the F-test) or by using a goodness-of-fit measure. In the latter case, to achieve parsimony, the quality of fit statistic is discounted for the number of unknown regression parameters. The Akaike Information Criterion (AIC) (Akaike, 1973) and the Bayesian Information Criterion (BIC) (Schwarz, 1978) are common choices of quality of fit measures for a statistical model. The AIC based variables selection process is one of the asymptotically efficient model selection tools (Hurvich & Tsai, 1989) that attempts to find the model that loses the least information, relative to how the data is actually generated (R. A. Berk, 2008, p. 34). The BIC variable selection method is one of a class of consistent model selection tools that finds the correct predictors if they are included within the set of models examined. A general recommendation for choosing between the AIC and the BIC methods is to use the AIC if the true model is unlikely to be within the set to be examined or the BIC if otherwise (R. A. Berk, 2008, p. 35). Following this rule, the AIC should be preferable to the BIC method in the context of hedge funds, since the true set of risk factors affecting hedge funds' returns is unlikely to be complete.

Accordingly, the next model that is examined is a linear regression model with AIC variable selection, or a stepwise linear regression model. This model seeks to identify an optimal subset of factors from the set of 14 variables, consisting of HL6 factors and other eight factors discussed above:

Model SLM14

$$\begin{aligned} R_{i,t} = \quad & \alpha_i + stepAIC(\beta_{i,1}SP500 + \beta_{i,2}USD + \beta_{i,3}BOND + \beta_{i,4}CREDIT \\ & + \beta_{i,5}GSCI + \beta_{i,6}DVIX + \beta_{i,7}SMB + \beta_{i,8}HML + \beta_{i,9}UMD \\ & + \beta_{i,10}EQINT + \beta_{i,11}EQEM + \beta_{i,12}LHYEILD + \beta_{i,13}BONDINT \\ & + \beta_{i,14}BONDCNV) + \varepsilon_{i,t} \end{aligned} \tag{5.4}$$

where $stepAIC$ refers to a stepwise variable selection procedure based on the AIC. The AIC variable selection procedure is given Appendix IV.

The objective of SLM14 model is to determine if statistical variable selection and customization of factors for each style may help to improve the hedge fund pricing model.

5.1.2 Generalized Additive Models

One of the major assumptions of multi-factor models is a linear relationship between hedge fund returns and returns of risk factor proxies. Since there are strong theoretical arguments and empirical evidence to suspect that the actual relationship is nonlinear (see Section 3.1), this thesis advocates for an alternative method which does not make any assumptions about the functional form of the model. The approach is known as a Generalized Additive Model (GAM) (Hastie & Tibshirani, 1990). A GAM represents a flexible nonparametric approach which allows the data to suggest an appropriate functional form. In a GAM the parametric coefficients $\beta_{i,j}$ of a multi-factor model (5.1) are replaced with variable-specific smoothing functions $f_{i,j}(\cdot)$:

$$R_{i,t} = \alpha_i + \sum_{j=1}^{N} f_{i,j}(F_{j,t}) + \varepsilon_{i,t} \tag{5.5}$$

where errors $\varepsilon_{i,t}$ are independent of the factors F_j, $j = 1, \ldots, N$; $E(\varepsilon_{i,t}) = 0$, $var(\varepsilon_{i,t}) = \sigma_i^2$; $f_{i,j}$ are univariate smooth functions or *smoothers*, defined such that $E(f_{i,j}) = 0$ in order to ensure model uniqueness. Each smooth function $f_{i,j}$ summarizes the trend of a response variable $R_{i,t}$ as a function of one predictor F_j. The trend is usually less variable than $R_{i,t}$ itself; hence the name smoother is used.

An important feature of a GAM in equation (5.5) is its additive structure. The additive form simplifies model interpretation: it makes possible to isolate the effect of each factor on the dependent variable, i.e. hedge fund return. Moreover, it helps to overcome the problem of high-dimensionality, also known as *the curse of dimensionality* (Bellman, 1961), i.e. the issue arising when estimation of a model occurs through sparse sampling in high dimensions. Since the response variable is modelled as the sum of univariate functions of predictors, the number of observations required to get variance-stable estimates grows only linearly with the number of predictor, i.e. N (Hastie & Tibshirani, 1990).

To estimate model (5.5) it is necessary to select a specific class of nonparametric smoothers $f_{i,j}$, referred further as *base smoothers* or *base learners*. Also, if statistical inference is required an assumption has to be made about the distributional properties of residuals $\varepsilon_{i,t}$, however it is not required for estimation.

In this thesis two classes of base smoothers are considered: loess smoother (Cleveland, 1979) and cubic splines (Reinsch, 1967). The next two sections discuss in more detail GAMs using loess and cubic spline smoothers and present models that will be tested.

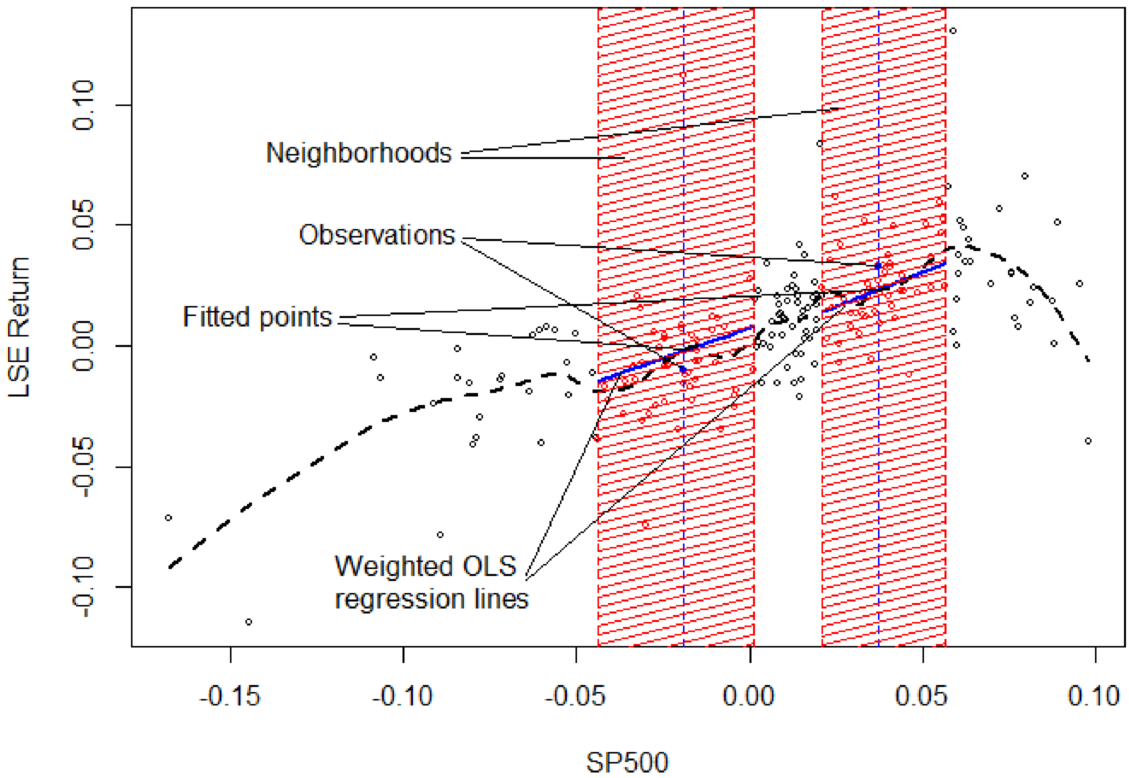
5.1.2.1 GAM with Loess Smoothers

The name loess is derived from locally weighted scatterplot smooth (Cleveland, 1979). Scatterplot smoothing is a generic name for nonparametric methods used to fit a function through the points of a scatterplot to best represent the relationship between the variables. Essentially a smoother yields a series of data reductions or summaries of the dependent variable, each specific to (possibly overlapping) regions of the space of predictors. A running mean is the simplest example of a scatterplot smoother.

A loess smoother works by fitting a series of locally weighted OLS regressions of one dependent variable and a single predictor and joining fits with straight lines. In other words, the loess smoother captures the relationship between the two variables by rolling a window of a certain size and fitting weighted OLS regressions. The amount of smoothing is controlled by the size of the window called *bandwidth* or *span*, which determines the proportion of neighbouring points included into the window. Bandwidth is the main parameter controlled by a data analyst to tune the degree of smoothness applied to the data by the loess smoother. Its choice is critical for the outcome and it is thoroughly discussed further in Section 5.1.2.1.1. In terms of the weight function applied to observations when estimating OLS regressions, a common choice is the tricube function[72]. However, in contrast to bandwidth, the weight function has a very limited effect on loess fit. As found in the literature in practice most of the popular weight functions produce similar results (R. A. Berk, 2008).

Figure 5.2 Smoothing with Loess

In the horizontal axis are returns of the S&P 500 index and in the vertical axis are the returns of the Long-Short Equity style. The shaded regions determine the neighbouring points of single observations (in this figure they correspond to bandwidth of 0.25 or 25%). The solid blue lines are the fit of locally weighted OLS regressions. The dashed black line is the resulting loess curve which passes through all the fitted points joined with straight lines.



The Figure 5.2 illustrates the main principles of scatterplot smoothing with loess. In this example returns of the Long-Short Equity style are considered to be a function of equity market returns. Loess smoother allows visualization of this function and the exploration of any nonlinear relationship between the style returns and factor returns.

[72] Other weight functions which can be used include the Gaussian kernel and the Epanechnikov kernel (Epanechnikov, 1969).

The loess smoothers with one dependent variable and a single predictor, as in Figure 5.2, are called bivariate loess smoothers. The bivariate loess procedure can be generalized and incorporated into a GAM with multiple predictors. In other words, hedge fund style returns can be considered as an additive function of multiple bivariate loess smoothers. This model fitting task is achieved by means of the *backfitting algorithm* (Breiman & Friedman, 1985). The backfitting algorithm is an iterative procedure that fits each bivariate loess smoother controlling for the effects of the smoothers. The technical details of loess smoothing as well as the backfitting algorithm are given in Appendix V. Complete reference on GAMs and loess smoothing can be found in the book by Hastie and Tibshirani (1990).

Similar to linear models HL6 and SLM14, a GAM using loess base smoothers is estimated with two sets of risk factors: HL6 variables and an extended set of 14 variables:

Model GAML6

$$\begin{aligned} R_{i,t} = \quad & \alpha_i + lo(SP500) + lo(USD) + lo(BOND) + lo(CREDIT) + lo(GSCI) \\ & +lo(DVIX) + \varepsilon_{i,t} \end{aligned} \qquad \textbf{(5.6)}$$

Model SGAML14

$$\begin{aligned} R_{i,t} = \quad & \alpha_i + stepAIC(SP500 + USD + BOND + CREDIT + GSCI + DVIX \\ & +SMB + HML + UMD + EQINT + EQEM + LHYEILD + BONDINT \\ & +BONDCNV, scope = \{1; linear; lo\}) + \varepsilon_{i,t} \end{aligned} \qquad \textbf{(5.7)}$$

where $lo(\dots)$ means that the term will be estimated using a loess smoother function.

Model GAML6 in equation (5.6) is a nonparametric version of the linear model HL6 given by equation (5.3). The nonparametric model GAML6 can be compared with the linear model HL6 to assess the importance of nonlinear effects in risk exposures and their impact on the accuracy of the hedge fund pricing model (see Section 5.1.5 for details on model comparison).

Model SGAML14 in equation (5.7) is a GAM with the AIC variable selection procedure. It is based on the same 14 factors as the stepwise linear model SLM14 (equation (5.4)). As indicated in the *scope* expression each term can enter the model as a constant[73], a linear predictor or a loess smooth function and the choice is governed by the AIC variable selection procedure. The AIC variable selection algorithm is analogous to one described for linear models (Algorithm IV.1 in Appendix IV), with the only difference that the regimen of each term is extended to incorporate the variable as a loess smooth function, i.e. $F_j = \{1, F_j, lo(F_j)\}, j = 1, \dots, N$.

Model SGAML14 is used to gauge simultaneously both how important are the nonlinearities in hedge fund returns and whether statistical variable selection methods can improve hedge fund pricing. It is achieved by comparing its performance with the performance of the linear model with variable selection SLM14 and the linear model without variable selection HL6.

It is important to note that nonparametric version of model FH7 (equation (5.2)) is not considered. FH7 model already contains three nonlinear factors, PTFSBS, PTFSFX and PTFSCOM (i.e. factors with nonlinear payoffs relative to their underlying instruments), which are supposed to capture any nonlinearities in risk exposures. Therefore, FH7 model does not imply any further enhancement to capture the nonlinearities. The authors of model HL6 in contrast specifically caution that it does not account for any nonlinearities (Hasanhodzic & Lo, 2007).

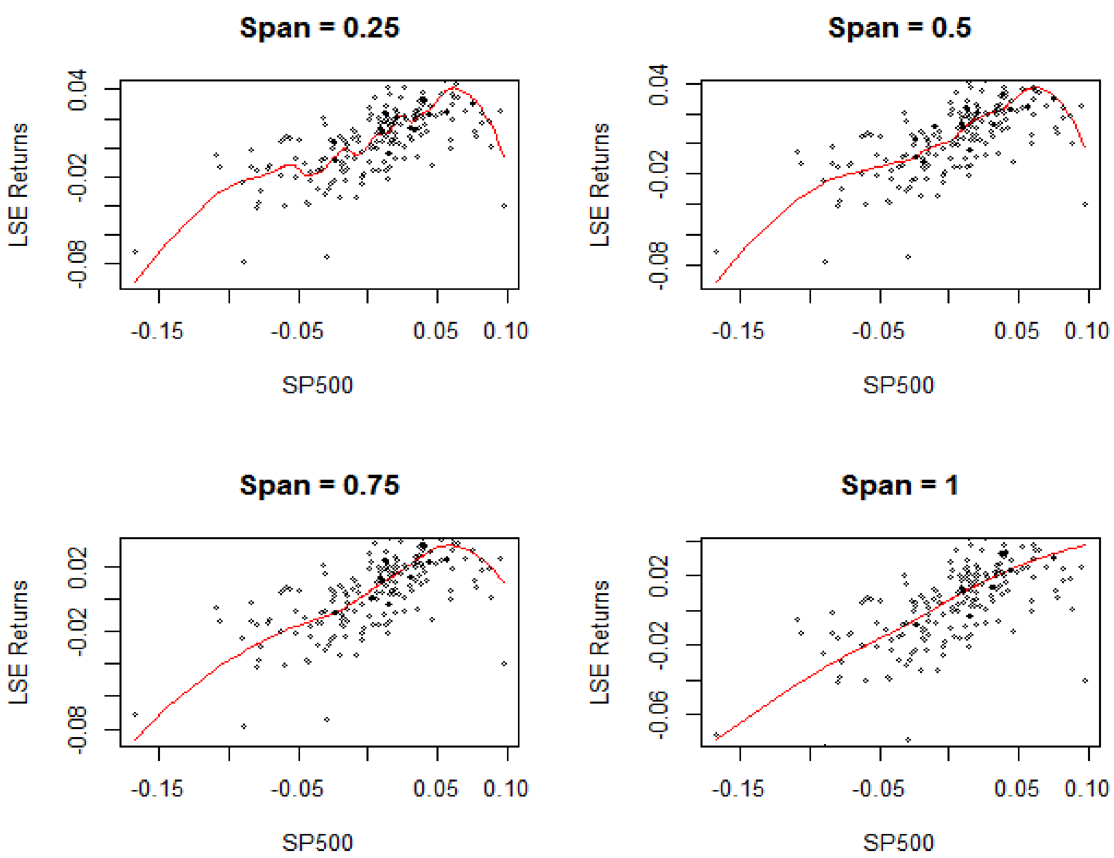
[73] When a term enters the model as a constant, it does not affect the model in any way, since the model already contains one constant term, i.e. the intercept. Hence, it is assumed that all constant terms are dropped from the model.

5.1.2.1.1 Choice of Bandwidth

The crucial parameter in a loess smoother is the bandwidth or span. Its effect on the shape of a loess smoothing function is illustrated below in Figure 5.3.

Figure 5.3 Effect of Bandwidth on Smoothness of Loess Fit

The figure demonstrates the fit of the loess function that models the returns of the Long-Short Equity style as a function of the S&P 500 index returns. Each graph corresponds to different value of the span parameter: 0.25, 0.5, 0.75 and 1.



As seen from Figure 5.3 the loess smoother fit is very sensitive to value of the bandwidth. The larger is the bandwidth, the smoother is the fit. The reason for that is twofold. Firstly, when the bandwidth increases, the size of the rolling window in the loess procedure also increases and the effect of noise in the data has proportionally less influence on the loess smoother (as idiosyncrasies cancel out each other). Secondly, larger bandwidth means less variation in the data captured by neighbouring rolling windows and less is the difference between the fits produced by local WLS regressions. Both of these factors tend to stabilize local regression lines and lead to smoother loess curves.

Furthermore, in observing the graphs that correspond to the bandwidth values of 0.25, 0.5 and 0.75, several potential issues are noted. In the middle of the graphs, the loess curves display higher irregularity. Instead of picking up the trend they seem to overfit the 'noise' in the data. In contrast to the middle part, the fit near the boundaries looks relatively smooth, because there are few observations there and adjacent points are connected with straight lines. However, even at the boundaries the shape of the curves is affected significantly by a few extreme outlier observations. These two issues indicate that the loess smoother with a small bandwidth tends to produce a curve that passes closer to the data and is more sensitive to outliers. The origins of these problems can be traced back to a well-known issue in statistics known as the *bias-variance trade-off* or the *bias-variance dilemma.*

The bias-variance trade-off is a problem arising when minimizing simultaneously model bias and variance (Claude & Geoffrey, 2011). The bias refers to the average model error across different training sets, while variance reflects the sensitivity of the model to small changes in the training set. In Figure 5.3 the bias is less and the fit is more accurate for smaller values of the bandwidth; however the variance is higher, because loess curves are more sensitive to outliers. In general, as the model complexity increases and the bandwidth decreases, the variance tends to increase and the bias tends to decrease. The bias and the variance cannot be minimized simultaneously. It is a goal of the data analyst to find a reasonable trade-off appropriate for the specific problem.

Accordingly to select the bandwidth parameter, an empirical analysis of GAMs with different values of bandwidth has been carried out. The models are tested in- and out-of-sample via a rolling window procedure with 1-month-ahead forecasts. Table 5.2 presents the in-sample (Panel A and Panel B) and out-of-sample (Panel C and Panel D) goodness-of-fit statistics of the six-factor and the 14-factor GAMs using loess smoothers with the bandwidth of 0.5 (in models GAML6-05 and SGAML14-05), 0.75 (GAML6-075 and SGAML14-075) and 1 (GAML6 and SGAML14). As clearly seen from the table, the less is the bandwidth, the more adaptable to the data the model is and the better is the fit in-sample. This why the six- and 14-factor models with the bandwidth of 0.5 outperform models with the bandwidth of 0.75 and 1. However, almost the opposite situation is observed out-of-sample: more flexible models with bandwidth of 0.5 and 0.75 on average and across most of the styles exhibit higher prediction error than models with the bandwidth of 1. The average out-of-sample root-mean-square error (RMSE) is 5.7% for SGAML14 model and 7.2% for SGAML14-05 model. This is due to the bias-variance trade-off explained above: higher flexibility decreases the bias, but increases the variance.

Based on the out-of-sample results, preference is given to models with a bandwidth of 1, since they are more robust to the presence of noise and outliers in the data. Also, this choice of bandwidth allows the minimization of type I error when testing the hypothesis for linearity, and, in applying the principal of “Occam's Razor”, will lead to simpler (i.e. smoother) models. Thus, in the rest of the thesis only models SGAML14 and GAML6 with bandwidth of 1 are considered.

Table 5.2 Performance of GAMs Using Loess Smoothers with Different Bandwidths

The table contains in-sample and out-of-sample root-mean-square error (RMSE) and mean absolute error (MAE) measures for GAMs using loess with the bandwidth of 1 (GAML6, SGAML14), 0.75 (GAML6-075, SGAML14-075) and 0.5 (GAML6-05, SGAML14-05). The bottom line in the tables contains the rank of each model based on the average value of RMSE (MAE). Models with lowest RMSE (MAE) for each style are shown in bold.

Panel A: In-Sample Root-Mean-Square Error

	Root-Mean-Square Error					
Style	**GAML6**	**SGAML14**	**GAML6-075**	**SGAML14-075**	**GAML6-05**	**SGAML14-05**
CA	0.043	0.036	0.040	0.029	0.038	**0.027**
DSB	0.104	0.079	0.098	0.067	0.093	**0.061**
EM	0.103	0.063	0.096	0.058	0.091	**0.054**
EMN	0.023	0.023	0.022	0.021	0.021	**0.021**
ED	0.036	0.028	0.032	0.024	0.030	**0.022**
FIA	0.035	0.032	0.031	0.025	0.029	**0.022**
GM	0.079	0.070	0.074	0.063	0.070	**0.058**
LSE	0.076	0.033	0.069	0.028	0.064	**0.025**
MF	0.101	0.096	0.089	0.088	0.083	**0.078**
MS	0.032	0.030	0.030	0.026	0.028	**0.024**
FoF	0.041	0.023	0.037	0.021	0.035	**0.019**
HFC	0.053	0.034	0.049	0.029	0.047	**0.026**
Average	0.060	0.046	0.055	0.040	0.052	**0.036**
Rank	*6*	*3*	*5*	*2*	*4*	***1***

Panel B: In-Sample Mean Absolute Error

	Mean Absolute Error					
Style	**GAML6**	**SGAML14**	**GAML6-075**	**SGAML14-075**	**GAML6-05**	**SGAML14-05**
CA	0.009	0.008	0.008	0.006	0.008	**0.006**
DSB	0.023	0.018	0.022	0.016	0.021	**0.014**
EM	0.021	0.014	0.020	0.013	0.019	**0.012**
EMN	0.005	0.005	0.005	0.005	0.005	**0.005**
ED	0.007	0.006	0.007	0.005	0.007	**0.005**
FIA	0.007	0.006	0.006	0.005	0.006	**0.005**
GM	0.016	0.015	0.015	0.014	0.014	**0.013**
LSE	0.015	0.008	0.013	0.007	0.012	**0.006**
MF	0.024	0.022	0.021	0.020	0.019	**0.018**
MS	0.007	0.006	0.007	0.006	0.006	**0.005**
FoF	0.009	0.005	0.008	0.005	0.007	**0.004**
HFC	0.011	0.008	0.010	0.006	0.009	**0.006**
Average	0.013	0.010	0.012	0.009	0.011	**0.008**
Rank	*6*	*3*	*5*	*2*	*4*	***1***

Panel C: Out-Of-Sample Root-Mean-Square Error

Style	GAML6	SGAML14	GAML6-075	SGAML14-075	GAML6-05	SGAML14-05
CA	0.070	**0.058**	0.069	0.062	0.065	0.067
DSB	0.119	0.111	0.129	**0.104**	0.132	0.121
EM	0.072	**0.057**	0.076	0.065	0.090	0.067
EMN	**0.038**	0.040	0.040	0.040	0.047	0.041
ED	0.039	**0.037**	**0.037**	0.038	0.043	0.072
FIA	0.062	**0.053**	0.072	0.058	0.090	0.068
GM	**0.059**	0.060	0.067	0.071	0.093	0.079
LSE	0.048	**0.033**	0.046	0.037	0.055	0.043
MF	0.114	0.118	0.121	**0.109**	0.146	0.120
MS	**0.043**	0.044	0.043	0.049	0.048	0.052
FoF	0.040	**0.034**	0.036	0.035	0.040	0.050
HFC	0.040	**0.036**	0.040	0.042	0.055	0.081
Average	0.062	0.057	0.065	0.059	0.075	0.072
Model Rank	*3*	***1***	*4*	*2*	*6*	*5*

Panel D: Out-Of-Sample Mean Absolute Error

Style	GAML6	SGAML14	GAML6-075	SGAML14-075	GAML6-05	SGAML14-05
CA	0.0125	**0.0111**	0.0127	0.0118	0.0124	0.0122
DSB	0.0236	0.0212	0.0240	**0.0199**	0.0259	0.0244
EM	0.0167	**0.0124**	0.0167	0.0140	0.0182	0.0141
EMN	0.0072	0.0073	0.0076	0.0071	0.0080	**0.0070**
ED	0.0087	**0.0080**	0.0084	0.0081	0.0093	0.0103
FIA	0.0109	**0.0101**	0.0117	0.0111	0.0131	0.0118
GM	**0.0128**	0.0129	0.0140	0.0152	0.0166	0.0162
LSE	0.0104	**0.0078**	0.0107	0.0084	0.0118	0.0087
MF	0.0280	0.0277	0.0277	**0.0254**	0.0297	0.0269
MS	0.0092	0.0093	**0.0090**	0.0095	0.0096	0.0101
FoF	0.0091	**0.0074**	0.0080	**0.0074**	0.0086	0.0081
HFC	0.0091	**0.0080**	0.0086	0.0089	0.0106	0.0113
Average	0.0132	**0.0119**	0.0133	0.0122	0.0145	0.0134
Model Rank	*3*	***1***	*3*	*2*	*6*	*5*

The downside of choosing a comparatively high bandwidth parameter setting is that it risks an overly smoothed fitting, which may result in some nonlinear risk exposures, especially in the tails of the return distributions, being missed. It is well known that dynamic trading and arbitrage strategies implemented by hedge funds may generate nonlinear exposures to negative tail risk (Brown, Gregoriou, & Pascalau, 2012; Fung & Hsieh, 1997a, 2001; Fung et al., 2008; Liang & Park, 2010; Mitchell & Pulvino, 2001). By setting a high value of bandwidth, a GAM may not be flexible enough to capture nonlinear exposures at the tails of the distribution. A counterargument is that extreme market scenarios are rare and it is difficult to ascertain whether risk exposure patterns observed at the tails are real or an artefact of noisy data and the small bandwidth choice.

Overall, when selecting the smoothing parameter it is worth remembering that with GAMs, the ability to make such a choice only makes explicit its effects, whilst with other methods, the choice is unavailable as it is already pre-set implicitly. For example, users of linear regression almost never question whether an assumption of perfect smoothness (i.e. a linear form) is reasonable (Beck & Jackman, 1998).

5.1.2.2 GAM with Smoothing Splines

Another common choice of base smoothers in GAMs are cubic splines (Reinsch, 1967). They are also tested in this thesis. Cubic splines owe their popularity to their mathematical properties which not only streamline computations, but also enable automatic selection of an optimal degree of smoothness and variable selection.

Cubic splines facilitate scatterplot smoothing in a very different way from loess functions. While loess smooth functions do not have an explicit mathematical representation, cubic splines do have a parametric representation. A cubic spline is a continuous smooth curve made up of sections of cubic polynomials, having a continuous first and second derivatives (Wood, 2006, p. 122). The continuity constraints on the first and second derivative mean that the fitted function looks visually smoother[74]. Accordingly, a smooth function $f(x)$ can be written with cubic splines in a short form as:

[74] As Hastie and Tibshirani (1990, pp. 22-23) note “our eyes are skilled at picking up second and lower order discontinuities, but not higher”.

$$f(x) = \sum_{k=1}^{q} b_k(x)\beta_k \qquad \textbf{(5.8)}$$

where polynomial functions $b_k(x)$ are known and can be found, for example, in Wood (2006, pp. 122-123). The points at which the polynomial sections are joined are known as the knots. The number of knots q determines the number of coefficients β_k or polynomial segments. q is also known as the *basis dimension*.

The parameterization of smooth functions with splines enables the conversion of a GAM into a linear regression model. The unknown parameters of this linear regression are then the spline coefficients β_k. The model can be estimated, for example, by the least squares procedure.

However, before the model can be estimated, the basis dimension q has to be selected. In contrast to loess smoothers where smoothness is controlled manually[75], splines provide for an automatic way to determine the optimal degree of smoothness. The idea is to keep the basis dimension q fixed at a size a little larger than it is believed to be necessary (see the next subsection 5.1.2.2.1 for details), but add a complexity penalty to the least squares fitting objective, i.e.:

$$\sum_{t=1}^{T} \left\{ R_{i,t} - \alpha_i - \sum_{j=1}^{N} f_{i,j}(F_{j,t}) \right\}^2 + \sum_{j=1}^{N} \lambda_{i,j} \int \left[f''_{i,j}(F) \right]^2 dF \qquad \textbf{(5.9)}$$

where the first sum in the equation (5.9) is the residual sum of squares (RSS) of the GAM and the second sum of integrated squares of second derivatives penalizes models that are

[75] It should be noted that there are methods to select the loess bandwidth parameter automatically based on certain criteria and cross-validation techniques. However, these methods are computationally and data intensive. Given that out-of-sample tests of GAMs with different values of the bandwidth show strong preference for the maximum value of the bandwidth, i.e. 1, automatic methods were not considered for GAMs involving loess functions.

too complex or "wiggly" and is called a *roughness penalty*. It follows from the equation (5.9) that the optimal trade-off between the model fit and the model smoothness can be determined automatically by solving the optimization problem (5.9) to find smoothing parameters λ_{ij} for each predictor, rather than controlling it manually by adjusting the basis dimension. $\lambda_{ij} \to \infty$ leads to a straight line estimate for $f_{i,j}$, while $\lambda_{ij} = 0$ results in unpenalized spline estimate[76]. Smoothing parameters λ_{ij} can be automatically estimated by minimizing the mean prediction error using the cross validation technique, an approach known as the generalized cross validation (GCV) score. The GCV helps to choose the optimal model complexity in a way that maximizes the ability of the model to predict data to which the model was not fitted.

Besides automatic selection of the degree of smoothness, the penalized least squares approach enables automatic variable selection. For that, the penalty term in equation (5.9) is modified in such a way that the smooth functions $f_{i,j}$ can be shrunk down to zero. The technique, known as the shrinkage procedure (Copas, 1983), was originally proposed for linear models and then adapted for GAMs by Marra and Wood (2011). This technique is a valid alternative to the conventional AIC and the BIC stepwise selection procedures in terms of prediction error and stability of parameters (Tibshirani, 1996). Giamouridis and Paterlini (2010) demonstrate that variable selection based on the shrinkage procedure for linear models produces more stable set of hedge funds' risk factors explaining the returns than stepwise techniques do.

[76] As $\lambda_{ij} \to \infty$, the roughness penalty dominates the criterion (5.9), making $f''_{i,j}(F) = 0$ yielding the least squares regression line as the solution function (since the second derivative of a linear function is zero). Conversely, as $\lambda_{ij} \to 0$, the roughness penalty disappears, allowing the RSS component of equation (5.9) to dominate; the resulting smooth function tends to a function that simply interpolates the data. In other words, $\lambda_{ij} \to \infty, \forall j = 1, \ldots, N$ leads to the smoothest possible fit, while $\lambda_{ij} \to 0, \forall j = 1, \ldots, N$ leads to the least smooth fit.

Once optimal smoothing parameters $\lambda_{i,j}$ are found, equation (5.9) can be estimated by penalized iteratively re-weighted least squares procedure (P-IRLS). The details can be found in Tibshirani (1990), Wood (2004) and Wood (2006).

A GAM using the cubic spline base smoothers is estimated with two sets of risk factors: HL6 variables and an extended variable set comprising of 14 variables:

Model GAMS6

$$\begin{aligned} R_{i,t} = \quad & \alpha_i + s(SP500) + s(USD) + s(BOND) + s(CREDIT) + s(GSCI) \\ & +s(DVIX) + \varepsilon_{i,t} \end{aligned} \qquad \textbf{(5.10)}$$

Model GAMS14

$$\begin{aligned} R_{i,t} = \quad & \alpha_i + \{s(SP500) + s(USD) + s(BOND) + s(CREDIT) + s(GSCI) \\ & + s(DVIX) + s(SMB) + s(HML) + s(UMD) + s(EQINT) \\ & + s(EQEM) + s(LHYEILD) + s(BONDINT) + s(BONDCNV), \\ & select = TRUE\} + \varepsilon_{i,t} \end{aligned} \qquad \textbf{(5.11)}$$

where $s(\dots)$ means that the term is estimated with a cubic spline smoother. The choice of the basis dimension of cubic splines is discussed in the next section 5.1.2.2.1. The two models are analogous to loess GAM models GAML6 (equation (5.6)) and SGAML14 (equation (5.7)). However, 14-factor GAMs using loess and spline smoothers employ different variable selection procedures: loess variable selection is based on the AIC criterion, while variable selection for cubic splines is based on the shrinkage procedure.

5.1.2.2.1 Choice of Basis Dimension

To estimate a GAM using cubic splines it is necessary to choose the basis dimension of cubic splines. However, as discussed above, this choice is not as critical as the choice of loess bandwidth parameter, because when fitting a GAM using splines the actual degree of smoothness is estimated automatically.

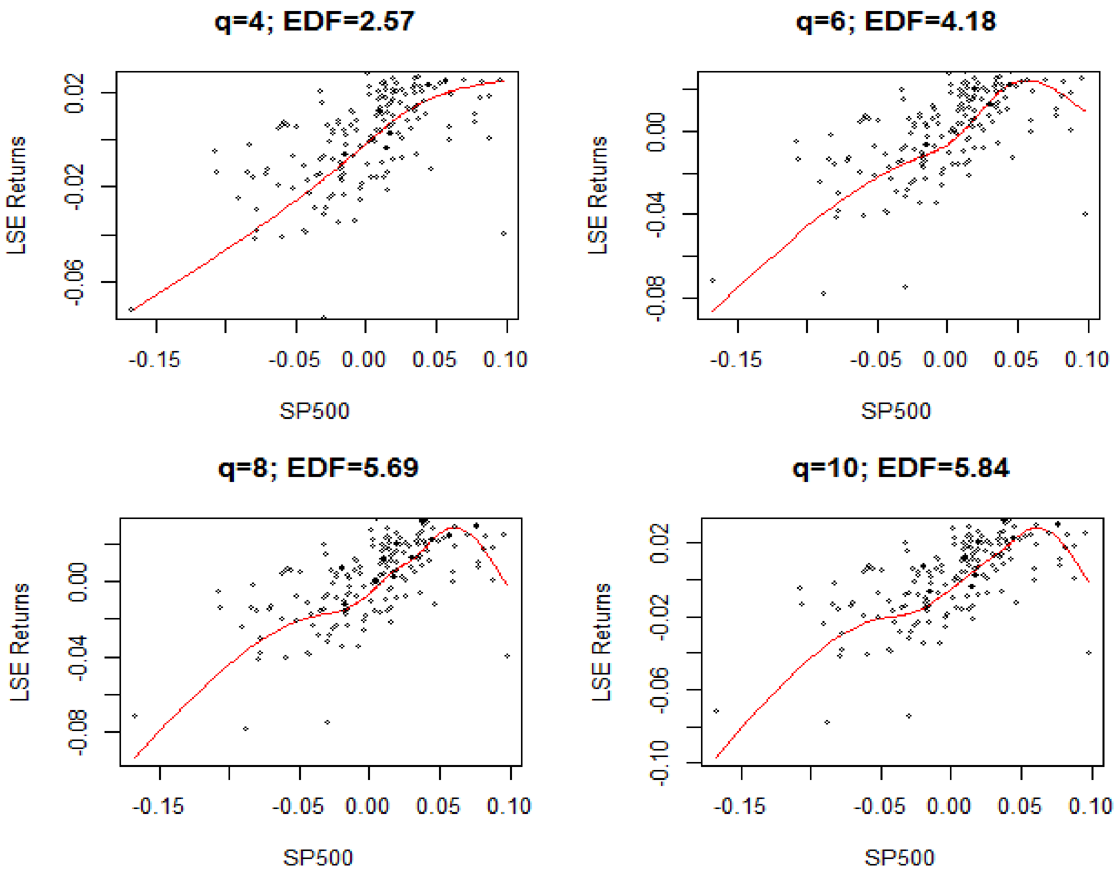
As discussed in Wood (2013, p. 15) in practice the basis dimension q (or $q - 1$, because one degree of freedom is usually lost to an identifiability constraint) sets the upper limit on the degrees of freedom associated with a spline smoother. The actual number of the effective degrees of freedom (EDF) is controlled by the degree of penalization selected during the fitting stage. Therefore, the exact choice of q, is not generally critical; it should be chosen to be large enough to be reasonably sure of having enough degrees of freedom to represent the underlying 'truth' reasonably well, but small enough to maintain reasonable computational efficiency.

It should be noted that the EDF of 1 implies a linear fit. Empirical tests with the hedge fund data performed in this study demonstrate that a reasonable range of values of q which allow capturing complex nonlinearities lies somewhere between 4 and 10. This range is in agreement with the value of q typically used in the literature[77]. Figure 5.4 provides an example of a GAM with a spline smoother and different basis dimensions.

[77] For instance, 4 is the default value of spline basis dimension in Hastie's implementation of a GAM in R package 'gam' (Hastie, 2013). Also, see other examples in Wood (2006).

Figure 5.4 Effect of Spline Basis Dimension on Smooth Functions

The figure demonstrates GAM cubic spline curves fitted to the returns of the Long-Short Equity style and the S&P 500 index returns. Each graph corresponds to a different value of the basis dimension, q: 4, 6, 8 and 10. The EDF is the Effective Degrees of Freedom associated with the fitted model.



As seen from Figure 5.4, spline curves tend to stabilize once the basis dimension q exceeds 6. The EDF values for $q = 8$ and $q = 10$ do not differ match. Thus, the optimal number of the degree of smoothness is close 6. Similar experiments conducted with other hedge fund styles and predictors produce similar results[78]. Accordingly, the basis dimension of 6 should suffice to provide enough flexibility for automatic selection of the degree of smoothing and avoid potential overfitting.

[78] These results are available from author upon request

5.1.3 Robust Linear and Generalized Additive Models with Component-Wise Gradient Boosting

Sections 5.1.1-5.1.2 discuss two approaches to modelling hedge fund returns: linear regression models and GAMs using loess and spline smoothers. One of the main assumptions of a linear regression model is an assumption of normal distribution of the residual term. However, it has been documented in earlier studies that return distributions of hedge funds have fatter tails than the tails in Gaussian distribution (Lo, 2001; Malkiel & Saha, 2005). As a result of violation of regression assumptions the validity of the model can be compromised, because under these circumstances the least squares estimates can be inefficient and biased. GAMs may also be affected by anomalies in the noisy data. Empirical tests (see Section 5.1.2.1.1) show that GAMs are sensitive to outliers in the data, which can lead to spurious nonlinear patterns and poor out-of-sample model performance. The problem of overfitting data is of more concern for GAMs than for linear models, because GAMs are more flexible and less robust than "absolutely smooth" linear regression models. In statistics, methods which perform effectively even when its variables or assumptions are altered are referred to as robust methods (Maronna, Martin, & Yohai, 2006). This section presents an approach, known as component-wise gradient boosting, which enables the development and robust estimation of linear regression models and GAMs.

To develop robust models it is important to understand why the models developed in previous sections may lack robustness. The reason is twofold. Firstly, these models are designed to fit expected mean of the conditional distribution $E(y|x)$ (i.e. expected value of hedge fund style returns given the values of underlying factors), while the mean statistic is typically quite sensitive to outliers and it is not considered as a robust measure of the central tendency of the distribution (Hastie, Tibshirani, & Friedman, 2004, pp. 308-311). Secondly, parameters of these models are estimated by the least squares procedure. It attempts to find such values of parameters which minimize the residual sum of squares (or penalized RSS in GAM which uses splines). However, the RSS is also known to be sensitive to outliers, because it is a measure of the second order. This amplifies the impact of any outlier point in the total RSS, more than any point in the middle range of the dataset.

The solution to this problem is to employ robust statistical measures. For example, instead of estimating the conditional mean and minimizing the squared error loss function, $L(y, f(x)) = (y - f(x))^2$ (i.e. the RSS), it is possible to estimate the conditional median and minimize the absolute loss function, $L(y, f(x)) = |y - f(x)|$. The median and the absolute deviation function are one of the most common robust alternatives to the mean and the RSS statistics. The absolute loss function does not place as much emphasis on observations with large absolute residuals $|y_i - f(x_i)|$ as the squared error loss function does. Thus, it is more robust and its performance does not degrades severely for long tailed error distributions (Hastie et al., 2004, p. 311). These properties can be particularly important in the hedge fund context.

Accordingly, along with the standard linear regression models and GAMs it is proposed to estimate the following robust versions of linear and generalized additive models of expected conditional median $median(y|x)$:

Model RLM6

$$\begin{aligned} R_{i,t} = \quad & \alpha_i + \beta_{i,1}SP500 + \beta_{i,2}USD + \beta_{i,3}BOND + \beta_{i,4}CREDIT + \beta_{i,5}GSCI \\ & +\beta_{i,6}DVIX + \varepsilon_{i,t} \end{aligned} \tag{5.12}$$

Model RLM14

$$R_{i,t} = \alpha_i + \beta_{i,1}SP500 + \beta_{i,2}USD + \beta_{i,3}BOND + \beta_{i,4}CREDIT + \beta_{i,5}GSCI + \beta_{i,6}DVIX + \beta_{i,7}SMB + \beta_{i,8}HML + \beta_{i,9}UMD + \beta_{i,10}EQINT + \beta_{i,11}EQEM + \beta_{i,12}LHYEILD + \beta_{i,13}BONDINT + \beta_{i,14}BONDCNV + \varepsilon_{i,t} \quad \textbf{(5.13)}$$

Model RGAMS6

$$R_{i,t} = \alpha_i + s(SP500) + s(USD) + s(BOND) + s(CREDIT) + s(GSCI) + s(DVIX) + \varepsilon_{i,t} \quad \textbf{(5.14)}$$

Model RGAMS14

$$R_{i,t} = \alpha_i + s(SP500) + s(USD) + s(BOND) + s(CREDIT) + s(GSCI) + s(DVIX) + s(SMB) + s(HML) + s(UMD) + s(EQINT) + s(EQEM) + s(LHYEILD) + s(BONDINT) + s(BONDCNV) + \varepsilon_{i,t} \quad \textbf{(5.15)}$$

Robust linear models RLM6 and RLM14 represent a median regression, i.e. a quantile regression (Koenker & Bassett, 1978) for the 50th percentile. Robust nonparametric models RGAMS6 and RGAMS14 are GAMs that use splines as the base smoothers and model expected median returns.

A number of methods exist to estimate these models. One of the ways is to use a *component-wise gradient boosting*[79] technique, an approach that provides a framework to estimate all these models and perform variable selection. The idea of the technique is to find the minimum value of the loss function by iteratively fitting the base learners to the negative gradient of the loss function and at each step select only one base learner that

[79] The method builds on several different techniques including boosting and gradient descent techniques with variable selection (Breiman, 1998, 1999; Friedman, 2001; Friedman, Hastie, & Tibshirani, 2000). For overview of boosting algorithms and loss functions, see, for instance, Bühlmann and Hothorn (2007).

provides a minimum to that loss function. By selecting at each iteration only one base learner, the algorithm carries out variable selection. Consequently, all four robust models (RLM6, RLM14, RGAM6 and RGAM14) attempt to find an optimal predictor set for each hedge fund style, i.e. these models involve automatic variable selection.

In a median regression, all the predictors enter the model in a linear form; therefore for its estimation base-learners are set to be linear functions of one variable. For GAMs a common choice of base learners is the penalized splines, since they possess superior theoretical properties that allow for efficient computation of the model parameters.

As discussed in Section 5.1.2 all the nonparametric methods have a tuning parameter which controls the degree of smoothness applied to the data: loess smoothers depends on the bandwidth parameter, cubic splines depend on the basis dimension parameter and smoothing parameter λ in the penalty term (though it is computed automatically as part of the P-IRLS procedure). In the gradient boosting technique, smooth functions adjust adaptively to minimize the loss function. The key factors which affect their shape are the learning rate ν and the number of iterations m_{stop} before the algorithm is terminated[80]. Lower learning rate increases the flexibility of the fitting process, but requires a greater number of iterations. A conventional approach is to keep the learning rate sufficiently small (i.e. $\nu < 0.01$, so that it does not have much impact on the outcome) and determine the optimal number of iterations via simulation techniques (R. A. Berk, 2008, p. 271). To choose an appropriate number of boosting iterations and prevent overfitting a common approach is to use cross-validated estimates of the empirical risk (R. A. Berk, 2008, p. 272). Accordingly,

[80] Converging properties of boosting procedures are not yet well understood; therefore, early stopping rule is usually determined via simulation techniques (Zhang & Yu, 2005)

a 25-fold bootstrap cross-validation method has been applied to choose the optimal number of iterations.

The details of the fitting procedure are outlined in Appendix VI.

5.1.4 Multivariate Adaptive Regression Splines

As discussed in the literature review (Sections 3.1.3.2-3) one of the alternatives to a linear regression model is a piecewise linear regression model, i.e. a model which consists of several linear parts joined together. In theory a piecewise linear regression model should provide an approximation of nonlinearities. In practice however, empirical evidence for the superior performance of piecewise linear regression models is inconclusive. Piecewise linear models with one break point do not outperform linear models out-of-sample, as shown in Amenc et al. (2010), whilst there is some evidence that suggests the more flexible threshold regression models with multiple thresholds are useful (Giannikis & Vrontos, 2011).

Accordingly, this section proposes a piecewise linear regression model as an alternative to a fully parametric linear regression model and a nonparametric GAM. One of the ways to fit a piecewise linear model is known as a multivariate adaptive regression splines (MARS) (Friedman, 1991) approach. Its main advantage is that it allows for an automatic identification of thresholds or kinks in the piecewise linear function and additionally it performs an automatic variable selection. That is why it seems reasonable to perform a comparison of a nonparametric GAM not only relatively to a linear regression model, but to a MARS as well.

A MARS approach fits the model using piecewise linear basis functions of the form $(x-t)_+$ and $(t-x)_+$, where "+" means positive part, i.e.:

$$(x-t)_+ = \begin{cases} x-t, if\ x>t \\ 0,\ \ otherwise \end{cases} \text{ and } (t-x)_+ = \begin{cases} t-x, if\ x<t \\ 0,\ \ otherwise \end{cases}$$

where t's are values of the knots located at each observed value x_{ij} of the predictors. The full collection of MARS basis functions is defined as:

$$C = \left\{ \left(X_j - t\right)_+, \left(t - X_j\right)_+ \right\}_{t \in \{x_{1j}, x_{2j}, \ldots, x_{Nj}\}, j=1,2,\ldots,p} \quad \textbf{(5.16)}$$

Accordingly, a MARS model is defined as follows:

$$f(X) = \beta_0 + \sum_{m=1}^{M} \beta_m h_m(X) \quad \textbf{(5.17)}$$

where functions $h_m(X)$ are either functions from space C, or a product of two or more such functions. Equation (5.17) presents a general MARS model. In this thesis a MARS model is constrained to be a first order polynomial, because a MARS model of the first order represents a piecewise linear function, which is of interest here. For that, products of basis functions are not permitted in the set C. Therefore, a MARS model consists of the sum of functions of the form $max(x-t,0)$ and $max(t-x,0)$, which are equivalent to option based factors considered earlier in the literature (Agarwal & Naik, 2004; Amenc et al., 2010; Diez de los Rios & Garcia, 2011). Thus, a MARS approach enables the comparison of a GAM with piecewise linear models.

Fitting a MARS model is a two stage process consisting of a forward and backward passes aimed at finding a parsimonious model, which minimizes generalized cross-validation score. The details of the procedure are described in Appendix VII.

A first order MARS model is estimated with two sets of risk factors: HL6 variables and an extended variable set of 14 factors:

Model MARS6

$$R_{i,t} = \alpha_i + SP500 + USD + BOND + CREDIT + GSCI + DVIX + \varepsilon_{i,t} \quad \textbf{(5.18)}$$

Model MARS14

$$\begin{aligned} R_{i,t} = \; & \alpha_i + SP500 + USD + BOND + CREDIT + GSCI + DVIX + SMB \\ & + HML + UMD + EQINT + EQEM + LHYEILD + BONDINT \\ & + BONDCNV + \varepsilon_{i,t} \end{aligned} \quad \textbf{(5.19)}$$

Both models allow for an arbitrary number of partitions of each term; thus, these models represent piecewise linear regressions. The number, location and slopes of linear segments are determined by the MARS algorithm[81]. The MARS algorithm also carries out an automatic variable selection.

5.1.5 Research Question 1: Modelling and Assessing Nonlinearities in Hedge Fund Indices

In the previous Sections 5.1.1-5.1.4, a number of approaches for modeling hedge fund returns were proposed. In total there are thirteen models (see Table 5.1), out of which five are linear and eight are nonlinear models. Among linear models are commonly used the seven-factor Fung and Hsieh (2004b) model, the six-factor Hasanhodzic and Lo (2007) model and a stepwise linear regression model with fourteen factors; among nonlinear models are GAMs using various types of base smoothers and estimation methods and a piecewise linear regression model.

To address the first research question about the presence of nonlinear risk exposures in aggregate hedge fund portfolios it is essential to establish that:

[81] This is why beta coefficients in Equation (5.18) and Equation (5.19) are omitted

1) There are nonlinear features in risk exposures of hedge funds; and these nonlinear patterns are genuine, i.e.:
2) Models which accommodate nonlinearities have better performance than linear models in-sample; and, most importantly,
3) Models which accommodate nonlinearities have better performance than linear models out-of-sample. Out-of-sample model performance is very important, because given the plethora of potential risk factors it is possible to find a set of variables and a nonlinear transformation function which would produce superior fit in sample. However, it can be easily checked if nonlinearities are genuine using an out-of-sample test. As explained earlier (Section 3.1.3) many hedge fund pricing models have not been thoroughly tested out-of-sample (e.g. the FH7 model).

To verify the first point, i.e. to examine statistical evidence of nonlinearities, three diagnostic tests are proposed:

- Visual examination of loess curves fitted to scatter plots of hedge fund returns and risk factor returns;
- the Ramsey (1969) RESET test of the nonlinear relationship between hedge fund returns and risk factor returns;
- Evaluation of nonlinear terms in GAMs.

A bivariate scatter plot is a standard approach in exploratory data analysis for visual examination of the pattern of the relationship between the two variables. Loess curves are also often fitted to the scatterplot to aid the analysis of the graphs. Scatterplots have been used to examine hedge fund risk exposures in Fung and Hsieh (2001), Favre and Galeano

(2002a), and Diez de los Rios and Garcia (2011), as well as to aid performance persistence analysis in Brown and Goetzmann (2003) and Jagannathan et al. (2010).

The RESET (Regression Equation Specification Error Test) test is a general specification test for the linear regression model. It tests whether higher order combinations of predictors help explaining the response variable. The RESET test applied to hedge fund data fits a linear regression to the returns of hedge funds using sequentially returns of all factors and second and third powers of explanatory variables. If regression coefficients for the second and third powers of the explanatory variable are statistically significant, then the hypothesis of a linear relationship between hedge fund returns and the variable is rejected. The RESET test compliments visual analysis and adds statistical credibility to the results.

Finally, GAMs also provide evidence of nonlinearities. As explained in Section 5.1.2.1, the AIC variable selection procedure in the 14-factor model for each potential variable has a choice to incorporate it in the model as a linear term, a nonlinear loess term or to drop the variable. Accordingly, nonlinear terms included in the model indicate potential nonlinear relationships.

To verify statistical evidence of nonlinearities, nonlinear models need to be compared with linear models. First of all, performance of the models is analysed in-sample. Models are estimated using the whole dataset and then compared based on standard goodness-of-fit measures including the Akaike Information Criterion (AIC) and R^2 coefficient. The AIC allows the comparison of models which are not necessarily nested. In contrast to R^2 coefficient which measures only the accuracy of fit[82], the AIC trades off the accuracy of fit and model complexity. It is defined according to the formula:

$$AIC = 2k - 2\ln(L) \tag{5.20}$$

where k is the number of parameters in the model, and L is the maximized value of the likelihood function for the estimated model (Akaike, 1974). For nonparametric models which rely on regularized (i.e. penalized) least squares method the number of parameters is usually replaced with the total number of effective degrees of freedom (EDF) (Ruppert, Wand, & Carroll, 2003). The total EDF measures the complexity of the fitted model and is interpreted as the equivalent number of parameters[83]. From Equation (5.20) it is clear that the more accurate and parsimonious model has lower value of the AIC. Therefore, based on the in-sample analysis the model with the lowest AIC should be preferred.

Next, an out-of-sample test of the models is performed. It is reasonable to expect that the model which correctly identifies and explains the sources of hedge fund returns should be able to produce good forecasts. It is well known in statistics that there is a higher risk of making spurious inferences and conclusions about [Granger] causality when out-of-sample verification is not employed (Ashley, Granger, & Schmalensee, 1980).

To test a model's performance out-of-sample, a rolling window procedure is applied to estimate the model and then perform an out-of-sample forecast. The estimation window includes 120 recent monthly observations. The size of the window is dictated by relatively

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[82] Adjusted R^2 coefficient cannot be calculated for nonparametric models, because the notion of the 'total number of parameters' necessary for its calculation cannot be applied to nonparametrically estimated smooth function.

[83] In a linear regression the total number of parameters can be calculated as the trace of the hat matrix H, $n = tr(H)$. Hat matrix H maps the vector of observed values to the vector of fitted values of the response variable, i.e. $\hat{y} = Hy$. By analogy in nonparametric smoothing techniques the EDF is defined as the trace of the smoother matrix S, where S similar to H transforms observed values to fitted values, i.e. $\hat{y} = Sy$. Therefore, the EDF can be viewed as generalization of the number of model parameters.

large number of observations required to fit nonparametric models. Given 120 observations, there are around 8 degrees of freedom per variable in 14-factor model which is in line with general GAM guidelines (Wood, 2006). There are no specific recommendations in the hedge fund literature about the size of the window. It is typically determined by practical considerations and data requirements of specific analytical tools used in the analysis. For example, Giamouridis and Paterlini (2010) utilize a 120-month estimation window, Giannikis and Vrontos (2011) employ recursive window expanding by one month starting from 192 months[84], Amenc, El Bied and Martellini (2003) estimate models based on 60 observations, while Hasanhodzic and Lo (2007) rely on a 24 month rolling window.

There are two main criteria to compare models out-of-sample: the annualized root-mean-square error (RMSE) and the mean absolute error (MAE):

$$Annualized\ RMSE_i = \sqrt{12\frac{\sum_{t=1}^{T}(R_{it} - \widehat{R_{it}})^2}{T}} \quad \textbf{(5.21)}$$

$$MAE_i = \frac{\sum_{t=1}^{T}\left|R_{it} - \widehat{R_{it}}\right|}{T} \quad \textbf{(5.22)}$$

where R_{it} is return of the hedge fund style i at time t; $\widehat{R_{it}}$ – forecasted return; and T is the number of out-of-sample forecasts. The model with the lowest value of the RMSE and the MAE is preferred.

Based on the results of in- and out-of-sample tests it is possible to evaluate statistical evidence of nonlinearities. If nonlinear models have less error in and out-of-sample, then nonlinear patterns are considered genuine.

[84] In Giannikis and Vrontos (2011) data sample starts in April 1990 and the first out-of-sample period begins in May 2005

5.2 Nonlinear Risk in Individual Funds

The previous section develops linear and nonparametric models utilized throughout the thesis; it also introduces tests that help to investigates nonlinear patterns in risk exposures of aggregate hedge fund style portfolios. This section discusses how nonlinearities are assessed in individual funds.

5.2.1 Classification of Funds by Form of Risk Exposures

As the study of Diez de los Rios and Garcia (2011) reveals, not all individual funds have asymmetric risk exposures. Therefore to examine nonlinearities at the fund level, models developed above are also fitted to the returns of individual funds. Due to the large number of funds and the large number of associated statistical tests required, the issues of data snooping and multiple hypotheses testing bias become problematic. To illustrate the problem, for a confidence level of 5% and 5,580 funds in the TASS dataset, testing for nonlinearities using a statistical test results in 279 funds being identified, purely by chance, as exhibiting nonlinear exposure to any of the variables. Clearly such an approach is not acceptable.

To solve this problem, the thesis follows the procedure proposed by Bollen (2013). Bollen (2013) examines those funds for which standard hedge fund pricing models do not perform well. To identify such funds the author uses the adjusted R^2 coefficient of a linear regression model and compares it with the critical value calculated via a bootstrap simulation procedure. The procedure enables Bollen (2013) to avoid the problem of data mining and classify funds into two groups: funds with insignificant adjusted R^2 coefficient or “zero R^2”

funds, and “positive R^2” funds. “Zero R^2” funds are funds for which standard linear regression models fail to explain the risk-return relationship.

In this thesis the classification procedure of Bollen (2013) is extended to examine three categories of funds: funds with only linear exposures to systematic risk (*linear funds*), funds with nonlinear risk exposures (*nonlinear funds*), and funds with insignificant or no exposure to systematic risk factors (*none* category).

The classification algorithm works as follows.

Algorithm 5.1. Classification of Funds by Form of Exposure to Systematic Risk

1) Fit a linear factor model to the returns of an individual hedge fund and calculate the adjusted R^2 coefficient, R^2_{lin};
2) Fit a nonlinear model to the residuals of the linear regression model obtained in step 1 and calculate approximate[85] adjusted R^2 coefficient R^2_{nonlin};
3) Based on critical values of the adjusted R^2 coefficient for linear and nonlinear models, i.e. $\hat{R}^2_{lin}$ and $\hat{R}^2_{nonlin}$ and using the classification rules below, determine the type of the fund:

$$Fund\ Type = \begin{cases} Linear, & R^2_{lin} > \hat{R}^2_{lin}\ AND\ R^2_{nonlin} \leq \hat{R}^2_{nonlin} \\ Nonlinear, & R^2_{nonlin} > \hat{R}^2_{nonlin} \\ None, & R^2_{lin} \leq \hat{R}^2_{lin}\ AND\ R^2_{nonlin} \leq \hat{R}^2_{nonlin} \end{cases} \quad \textbf{(5.23)}$$

[85] For the nonlinear model approximate adjusted R^2 coefficient is calculated here in the same way as for the linear model, i.e. $Adj.R^2 = 1-(1-R^2)\frac{n-1}{n-p-1}$, where n is the total number of observations and p is the total number of variables. It is necessary to understand that the number of variables does not reflect fully the complexity of the nonlinear model. See the discussion on the number of parameters and the EDF above in Section 5.1.5. However, empirical tests show that the choice of the goodness-of-fit measure used for classification of funds is not critical and leads to similar results when using the AIC and the BIC.

where a $'Linear'$ type refers to funds with significant linear exposures to systematic risk; a $'Nonlinear'$ type refers to funds with any significant nonlinear risk exposure; and a $'None'$ type refers to funds with insignificant and no systematic risk exposure.

Critical values of the adjusted R^2 coefficients $\hat{R}^2_{lin}$ and $\hat{R}^2_{nonlin}$ are determined via a simulation procedure similar to that used in Bollen (2013). Initially 1,000 random samples of 60 observations each are drawn from a standard normal distribution, a student *t*-distribution with one and two degrees of freedom, and a pooled distribution of all hedge fund returns via bootstrapping with resampling. A Student *t*-distribution is used since it has heavier tails than the standard normal distribution and thus should match better real hedge fund distributions exhibiting leptokurtic features. The bootstrapped series represents random returns drawn directly from the empirical distribution of hedge fund returns and that reflect the historical distribution of returns. In the next step, a linear regression model is fitted to randomly generated series of hedge fund returns, and a nonlinear model is fitted to the residuals of the linear regression model. The adjusted R^2 coefficients are calculated for both the linear and the nonlinear models. Finally, the empirical distributions of R^2 coefficient are constructed and 95^{th} percentiles are estimated. Then, the critical R^2 value for the linear and the nonlinear model is calculated as the average 95^{th} percentile calculated across the fitted regressions for the normal, student t distribution, and bootstrap generated random return series.

Several caveats are in place regarding the classification procedure. Firstly, the choice of the linear and nonlinear models may influence the outcome of the classification. For instance, in Bollen (2013) the number of "zero R^2" funds varies from 27.5% according to the 14-factor model to 36.6% for the seven-factor Fung and Hsieh (2004b) model. To address this concern only the “best” linear and nonlinear models are employed, i.e. those models which have the lowest out-of-sample error as identified in the first part of the thesis. Also, to account for possible variation of results related to different sets of variables used in the models, two sets of factors are utilized, the HL6 variables and the extended set of 14 factors.

Secondly, due to concurvity between the variables[86] and short return histories some funds may exhibit spurious nonlinear patterns. However, this problem should be mitigated by applying a stringent procedure used to calculate critical values of R^2 based on simulation methods. Essentially the simulation technique presented above represents an example of the “reality check” described in White (2000) to guard against data snooping.

Thirdly, drawing from the ideas of Bollen (2013), funds from the ‘None’ subset cannot be considered completely market-neutral despite having insignificant linear and nonlinear adjusted R^2 coefficients. This is because multi-factor models are able to capture only the most common sources of systematic risk, whilst some other important risk variables may be missed. There is no doubt however that these funds carry much less exposure to systematic risk than funds from the ‘Linear’ and the ‘Nonlinear’ subsets; thus, they fit closer the original concept underlying hedge funds as market neutral investment vehicles. Bollen (2013) finds that “zero R^2” funds on average have half systematic risk of “positive R^2” funds. Given that classification scheme in Algorithm 5.1 accounts not only for linear exposures but for nonlinear exposures as well, funds in the ‘None’ subset should have even less systematic risk than in Bollen’s (2013) “zero R^2” group.

[86] Concurvity is the nonparametric analogue of multicollinearity

5.2.2 Research Question 2: Assessing Nonlinearities in Individual Funds

After classification of funds is performed, three questions related to the assessment and evaluation of nonlinearities in individual funds formulated in Section 3.1.6 can be addressed. The first question RQ2.1 is related to the presence of nonlinearities in individual funds. Accordingly, the number of funds classified as *nonlinear* defines how common nonlinear risk exposures are across funds within each hedge fund category.

Next, to address the research question RQ2.2 it is necessary to compare performance characteristics of funds from different subsets, i.e. funds with linear, nonlinear and insignificant exposure to systematic risk. The following performance measures calculated as averages across all funds within subsets are examined: the Sharpe ratio (Sharpe)[87], the expected shortfall (ES), alpha relative to all funds within the style (Alpha), and the appraisal ratio (Appraisal). These measures are calculated as follows:

$$Sharpe = \frac{E(r_t)}{\sigma(r_t)} \quad \textbf{(5.24)}$$

$$ES = \frac{1}{\alpha}\int_0^{\alpha} VaR_{\gamma}(r_t)d\gamma \quad \textbf{(5.25)}$$

$$Alpha = E(r_t^{sub} - \overline{r}_t) \quad \textbf{(5.26)}$$

$$Appraisal = \frac{Alpha}{\sigma(\varepsilon_t)} \quad \textbf{(5.27)}$$

[87] As a matter of convention, throughout this thesis the Sharpe ratio is defined as the ratio of the average annualized return to the annualized standard deviation. In the original definition of the Sharpe ratio, the numerator is the excess return of the fund, in excess of the risk-free rate.

where $E(r_t)$ is the annualized expected return and $\sigma(r_t)$ is the annualized standard deviation of returns; $VaR_\gamma(r_t)$ is the value at risk measure at confidence level γ; r_t^{sub} is the return of a fund from one of three subsets (i.e. 'Linear', 'Nonlinear', and 'None') at time t; $\overline{r}_t$ is the average return of all funds in the category at time t; $\sigma(\varepsilon_t)$ is the standard deviation of residuals from the regression of the fund return on the average return of all the funds in the category.

The Sharpe ratio is the best known (Modigliani & Modigliani, 1997) and the best understood risk-adjusted performance measure (Lo, 2002). It is a model free measure as it does not require an appropriately defined risky benchmark. Also, its advantage is that a statistical test is available to test the difference between the Sharpe ratios of funds from different subsets. Specifically, following Cumming, Helge and Schweizer (2013), Titman and Tiu (2011) and many others the Jobson and Korkie (1981) test with the correction of Memmel (2003) is used to statistically test the difference between the Sharpe ratios. In this test all the variances and the covariances are adjusted for serial autocorrelation using Newey-West estimators with 23 lags.

The expected shortfall, also known as Conditional Value at Risk (CVaR), average value at risk and expected tail loss, corresponds to the mean of losses exceeding the VaR[88]. While the VaR focuses only on the frequency of extreme events, the ES accounts for both frequency and size of losses in case of extreme events. The ES is a useful characteristic for hedge funds, because it provides a quantitative measure of the negative tail of the return distribution. It is particularly interesting to compare tail risk of funds with linear and nonlinear exposures, as nonlinear features are typically observed at the boundaries of the return distribution. As

[88] Throughout this study the VaR refers to the Cornish-Fisher estimate of VaR

demonstrated earlier in the literature ignoring the tail risk of hedge funds can result in substantial underestimation of losses during large market downturns (Agarwal & Naik, 2004). The lower is the ES, the lower is the loss that is expected in extreme market scenarios.

The last two measures, alpha and the appraisal ratio are defined following Agarwal and Naik (2000a). Alpha is measured as the return of a fund from the particular subset (i.e. 'Linear', 'Nonlinear' and 'None') and hedge fund category minus the average return of all hedge funds within the same category. This definition facilitates the analysis of performance of funds with different forms of risk exposures relative to their peers in the same hedge fund category. However, alpha measure can be misleading if different subsets of funds employ different degrees of leverage to scale up their alphas and improve relative performance (Park & Staum, 1998). Therefore, an alternative measure which accounts for leverage and known as the appraisal ratio is used as well. It is defined as the alpha divided by the residual standard deviation resulting from a linear regression of the hedge fund return on the average return of all hedge funds from the same style. The appraisal ratio takes into account the differences in the volatility of returns and, thus, it is leverage-invariant. The higher is the alpha and the appraisal ratio, the better is the performance of the fund in the subset relatively to other funds from other subsets.

Finally, research question RQ2.3 focuses on the persistence of the form of fund's risk exposures (see Section 3.1.6). This is an important question, because it helps to clarify whether knowledge of fund's form of risk exposures in the past can help to make better investment decisions in the future. Following the literature on performance persistence of hedge funds (Fung et al., 2008) and private equity funds (Kaplan & Schoar, 2005) persistence of the form of risk exposures is analysed in a two-period setting by calculating transition probabilities. A transition probability determines the likelihood of a fund moving from one subset to another in the next period. Transition probabilities are calculated using a pair of five-year rolling windows according to the following formula:

$$p_{i,j} = \frac{N_{i,j}}{N_{i+}}, i,j = 1,2,3 \tag{5.28}$$

where i refers to the subset ('Linear', 'Nonlinear' and 'None') a fund belongs to in the first period t_1, and j refers to the subset in the next period t_2; $p_{i,j}$ is the transition probability of a fund from the subset i in period t_1 to the subset j in period t_2; $N_{i,j}$ is the number of funds in the subset i in period t_1 moved to the subset j in period t_2; and N_{i+} is the total number of funds in the subset i in period t_1, i.e. $N_{i+} = \sum_j N_{i,j}$. The main focus is on three probabilities $p_{i,j}$ when $i = j$, and particularly on the probability $p_{2,2}$, i.e. the probability that a nonlinear fund remains in the nonlinear subset in the next period.

Also, it is a standard approach in performance persistence literature to compliment the analysis of contingency tables and transition probabilities with a formal test on persistence, such as the Chi-squared test and the cross-product ratio (CPR) test (Agarwal & Naik, 2000a; Edwards & Caglayan, 2001). However, these tests are generally used for two nominal variables with two different values, e.g. for a two-way winner-looser contingency table. They cannot be directly applied to nominal variables with three values. One of the alternative measures and tests that can be applied to variables with any number of categories is the Cohen's Kappa coefficient (Cohen, 1960) (thereafter, kappa). Originally the coefficient was proposed to measure the agreement between the two raters categorizing a sample on a nominal scale. The basic idea behind the kappa is that some of the apparent classification accuracy given by naïve measures (such as transition probabilities $p_{i,j}, i = j$)

could be due to chance. That is why it is generally thought to be a more robust measure than a simple percentage agreement measure, such as transition probabilities. In a similar vein to measuring agreement between the two classifications the kappa coefficient can be applied to gauge the agreement or persistence of the form of a fund's risk exposures over two consecutive periods. It is calculated according to the formula (Rossiter, 2004):

$$\kappa = \frac{\sum_{i=j} p_{ij} - \sum_i p_{i+} \cdot p_{+i}}{1 - \sum_i p_{i+} \cdot p_{+i}}, \tag{5.29}$$

where

$$p_{i+} = \frac{N_{i+}}{n}, \qquad p_{+i} = \frac{N_{+i}}{n}, \quad N_{i+} = \sum_j N_{i,j}\,, \qquad N_{+i} = \sum_j N_{j,i}, \;\; n = \sum_{i,j} N_{i,j} \tag{5.30}$$

The standard error of the kappa coefficient is given, for example in Rossiter (2004) by formula 18. Accordingly, statistical significance of the kappa coefficient is tested via *t*-test.

Also, the conditional kappa coefficient can be calculated for each subset separately:

$$\kappa_{i+} = \frac{\frac{p_{ii}}{p_{i+}} - p_{+i}}{1 - p_{+i}}, \tag{5.31}$$

The idea is to apply the conditional kappa to check the difference between persistence of the linear, the nonlinear and the risk-neutral profiles of hedge funds.

The values of the kappa and the conditional kappa coefficients can be roughly interpreted in the following manner (Altman, 1990):

Table 5.3 Interpretation of Cohen's Kappa

Value	Strength of Agreement
<0.20	Poor
0.21-0.40	Fair
0.41-0.60	Moderate
0.61-0.80	Good
0.81-1.00	Very good

In summary, κ is used to measure the degree of persistence of funds' form of risk exposures.

5.3 Hedge Fund Replication

The first two parts of this study investigate the evidence of nonlinearities in hedge fund portfolios and individual funds. This section develops methods related to the third area of investigation, i.e. hedge fund replication. The main idea is that if nonlinearities are important for hedge fund pricing, then nonlinear hedge fund clones will be more accurate than linear clones. Comparison of the tracking accuracy and performance of linear and nonlinear replicators can help to understand the significance of nonlinearities from an economic perspective, rather than just in purely statistical terms. Accordingly, Sections 5.3.1 and 5.3.2 describe the methodology used for construction of linear and nonlinear clones respectively; and Section 5.3.3 outlines metrics and tests used to evaluate and compare different clones.

5.3.1 Constructing Linear Replicating Portfolios

A straightforward way to construct a linear replicating portfolio of a hedge fund style index is to use one of linear factor models described earlier. As results related to the first research question show (see Chapter 6), a stepwise linear regression model SLM14 has the lowest out-of-sample error among linear models introduced in Section 5.1.1. Thus, this model is used to construct linear clones. In addition, Hasanhodzic and Lo (2007) model HL6 is also applied and used as a benchmark model, because this model has been used for replication in earlier studies (see Section 5.1.1).

Two linear models SLM14 and HL6 are estimated via a rolling window procedure under the constraint that the intercept term equals zero. The intercept term represents fund manager' alpha, and since linear clones replicate only the part of returns attributed to alternative beta, alpha should be omitted. The next step is to compute a vector with portfolios weights according to the following formulas:

$$\boldsymbol{w}_i^{SLM14} = \left\{1 - \sum_j \beta_{i,j}\,, \beta_{i,j}\right\}, j = 1, \ldots, 14 \tag{5.32}$$

$$\boldsymbol{w}_i^{HL6} = \left\{1 - \sum_j \beta_{i,j}\,, \beta_{i,j}\right\}, j = 1, \ldots, 6 \tag{5.33}$$

where $\beta_{i,j}$ is a regression coefficient for hedge fund style i and risk factor j. The first component of these vectors, i.e. $1 - \sum_j \beta_{i,j}$, refers to the weight of the risk-free asset in the replicating portfolio. The risk free asset is added to enable portfolio leverage, because hedge funds often use leverage. An alternative way to account for leverage is to re-scale portfolio weights so that the in-sample volatilities of the benchmark and the clone are equalized, subject to the constraint that beta coefficients add up to one (Hasanhodzic & Lo, 2007, pp. 20-21), i.e.:

$$\boldsymbol{w}_{i,j} = \gamma_i \beta_{i,j}, \quad \gamma_i = \frac{\sqrt{\sum_{t=t}^{T} \left(r_{i,t} - \bar{r}_i\right)^2 / (T-1)}}{\sqrt{\sum_{t=t}^{T} \left(\hat{r}_{i,t} - \bar{\hat{r}}_i\right)^2 / (T-1)}}, \quad \sum_j \beta_{i,j} = 1 \tag{5.34}$$

where $r_{i,t}$ is the return of the hedge fund style index i at time t; $\bar{r}_i$ is the average return of the hedge fund style index i; $\hat{r}_{i,t}$ is the replicated hedge fund return for style index i at time t before the renormalization; and $\bar{\hat{r}}_i$ is the average replicated hedge fund return for style index i at time t before the renormalization.

Given the vector of weights the return of the replicating portfolio in the next out-of-sample period (i.e. next month) is calculated as follows:

$$\hat{\boldsymbol{r}}_{i,t+1}^{Clone} = \boldsymbol{F}_{\boldsymbol{t+1}} \times \boldsymbol{w}_i \qquad \textbf{(5.35)}$$

where $\boldsymbol{F}_{\boldsymbol{t+1}}$ is a vector with factor returns in period $t+1$, $\boldsymbol{w}_i$ equals $\boldsymbol{w}_i^{SLM14}$ for the 14-factor model, and $\boldsymbol{w}_i^{HL6}$ for the six-factor model.

5.3.2 Constructing Nonlinear Replicating Portfolios

Since hedge funds' risk exposure may have a nonlinear form, theoretically tracking accuracy of linear clones can be improved by capturing nonlinear patterns in residual variation of returns of linear clones. As results in Chapter 6 further reveal, the nonlinear model SGAML14, i.e. a stepwise GAM using loess smoothers, is able to capture nonlinearities and produce lower out-of-sample error than all other linear and nonparametric models. Therefore, SGAML14 model is used to test a nonlinear approach to hedge fund replication. Also, since linear clones rely on HL6 model, the six-factor GAM using loess smoothers (i.e. GAML6 model) is also considered.

Construction of a nonlinear replicating portfolio involves four steps:

1. Fit a linear model;
2. Calculate portfolio weights;

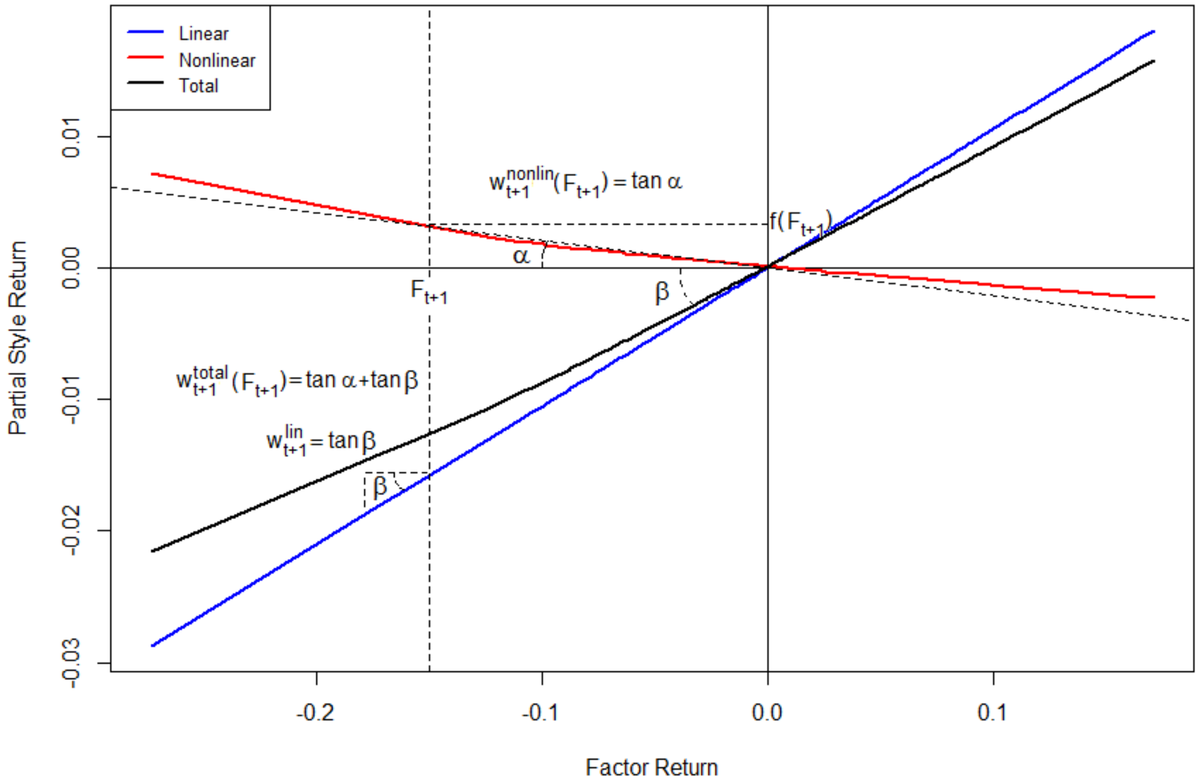
3. Fit a nonlinear model to the residuals of the linear model;
4. Update weights.

The reason for fitting the nonlinear model to the residuals of the linear model is the following. To ensure the unicity of a GAM of the form $R_{i,t} = \alpha_i + \sum_{j=1}^{N} f_{i,j}(F_{j,t}) + \varepsilon_{i,t}$ the intercept term α_i and smoothing terms $f_{i,j}$ are defined such that $\alpha_i = E(R_{i,t})$ and $E(f_{i,j}) = 0$. If α_i is a free parameter, the smoother functions $f_{i,j}$ will be defined only up to an additive constant, and the GAM will not be unique. These constraints imposed on the GAM mean that a GAM approach models only the deviation of the dependent variable from its mean value, i.e. $E(R_{i,t})$. Therefore, to replicate hedge fund returns it is proposed first to fit a linear model and capture part of the returns that can be attributed to a fund's linear exposure to systematic risk, and then fit a GAM to the residuals of the linear model to capture the residual variation due to nonlinear exposure to systematic risk. If nonlinear patterns are genuine, the nonlinear approach should lead to higher tracking accuracy of replicating portfolios out-of-sample than the linear approach, since it captures more subtle higher order nonlinear effects in risk exposures. This represents a more stringent test of hedge fund nonlinearities than most of the extant literature provides.

The first two steps in construction of a nonlinear replicating portfolio repeat the procedure outlined in the previous section used to construct a linear clone. In the next two steps the weights in the replicating portfolio are refined in accordance with the nonlinear model as illustrated in Figure 5.4.

Figure 5.5 Weights Calculation in a Nonlinear Replication Approach

The figure illustrates calculation of weight of an asset in replicating portfolio according to the linear model and the nonlinear model fitted to the residuals of the linear model. The linear regression line is depicted in blue, nonlinear curve is in red and their sum is in black. F_{t+1} is the value of the factor in period $t+1$ and $f(F_{t+1})$ is the corresponding value of the smoother; α is the smaller angle between the horizontal axis and the line passing through the origin and point $(F_{t+1}, f(F_{t+1}))$; β is the angle between the linear regression line at point $F = F_{t+1}$ and the horizontal line.



According to a linear regression model, portfolio weights in an out-of-sample period $t+1$ equal to the beta coefficients of the model estimated up to period t (see equations (5.32)-(5.33)). In mathematical terms a single beta coefficient equals to the gradient of the projection line of the linear regression plane on the plane $(\mathrm{R_i}, \mathrm{F_j})$ at point $\mathrm{F_j} = \mathrm{F_{j,t+1}}$ i.e. tangent of the angle β in Figure 5.5:

$$w_{j,t+1}^{linear}(F_{j,t+1}) = \tan\beta_j \tag{5.36}$$

Since the projection of the linear regression plane is a straight line, its gradient is constant and does not depend on F_j:

$$w_{j,t+1}^{linear}(F_{j,t+1}) = w_{j,t+1}^{linear} \tag{5.37}$$

In other words, to determine weights in an out-of-sample period $t+1$, only information up to time t is necessary, because the gradient of a straight line is constant and time invariant. The main property of weights defined in equation (5.36) is that if a linear model perfectly models and predicts hedge fund returns, then returns of the linear replicating portfolio at time $t+1$, R_{t+1}^{linear}, will exactly match the realized hedge fund return:

$$R_{t+1}^{linear} = \sum_j w_{j,t+1}^{linear} \times F_{j,t+1} = R_{t+1} \tag{5.38}$$

In a nonlinear model weights can be defined by analogy with a linear model in such a way that the main property (5.38) holds, i.e.:

$$w_{j,t+1}^{nonlinear}(F_{j,t+1}) = \tan \alpha_{j,t+1} \tag{5.39}$$

where $\alpha_{j,t+1}$ is the smaller angle between the horizontal axis and the line passing through the origin and the point $\left(F_{j,t+1}, f_j(F_{j,t+1})\right)$, where $f_j(F_{j,t+1})$ is the value of the smooth function corresponding to factor j realized at time $t+1$. Nonlinear weights defined by equation (5.39) indeed satisfy the property (5.38), if the nonlinear model perfectly predicts hedge fund returns:

$$\begin{aligned} R_{t+1}^{nonlinear} &= \sum_j w_{j,t+1}^{nonlinear}(F_{j,t+1}) \times F_{j,t+1} = \sum_j \tan \alpha_{j,t+1} \times F_{j,t+1} = \\ &= \sum_j \frac{f_j(F_{j,t+1})}{F_{j,t+1}} \times F_{j,t+1} = \sum_j f_j(F_{j,t+1}) = R_{t+1} \end{aligned} \tag{5.40}$$

where the last equality holds when the error term in a nonlinear model is zero.

The crucial difference between the nonlinear weights and linear weights is that the former depend on the realized values of the underlying factors in period $t+1$, because smooth functions f_j may have any form, not necessarily linear and the angle $\alpha_{j,t+1}$ depends on $F_{j,t+1}$. To put it simply, the gradient of a nonlinear function is not constant; hence nonlinear weights are not time-invariant, in contrast to linear weights. Therefore, return predictions from nonlinear clones rely upon a forecast of underlying factors and that cannot be often accurately achieved in practice. There exist other ways to replicate smooth functions f_j synthetically. For example Bertsimas, Kogan and Lo (2001) propose a method called "epsilon-arbitrage" strategies which allows replicating payoff functions with very general profiles. However, this issue is beyond the scope of this thesis.

Given this caveat, returns of nonlinear replicating portfolios throughout the thesis refer to hypothetical returns, or a model output, rather than a true portfolio returns which can be realized in practice. The main emphasis in this thesis is not to develop a viable trading strategy, but rather to validate the hypothesis that hedge funds do have nonlinear risk exposures which are of economically significant magnitude. Hypothetical nonlinear clones allow this hypothesis to be tested.

The final step to construct nonlinear replicating portfolios involves calculation of the total weight for each asset by adding together linear and nonlinear weights:

$$\boldsymbol{w}_i^{SGAML14} = \left\{1 - \sum_j \left(w_{j,t+1}^{linear} + w_{j,t+1}^{nonlinear}\right), w_{j,t+1}^{linear} + w_{j,t+1}^{nonlinear}\right\}, j = 1, \dots, 14 \quad \textbf{(5.41)}$$

$$\boldsymbol{w}_i^{GAML6} = \left\{1 - \sum_j \left(w_{j,t+1}^{linear} + w_{j,t+1}^{nonlinear}\right), w_{j,t+1}^{linear} + w_{j,t+1}^{nonlinear}\right\}, j = 1, \dots, 6 \quad \textbf{(5.42)}$$

where the first element in the vector refers to the weight of a risk-free asset in the replicating portfolio. In equation (5.41) linear weights are calculated using model SLM14 with omitted intercept and nonlinear weights are calculated using model SGAML14. In equation (5.42) HL6 model without the intercept term and GAML6 model are used to estimate linear and nonlinear weights respectively. Once weights are calculated the formula (5.35) can be applied to obtain the returns of a nonlinear replicating portfolio.

5.3.3 Research Question 3: Hedge Fund Replication and Nonlinear Risk

The previous two sections explain the process of constructing linear and nonlinear replicating portfolios. This section outlines the methodology used to evaluate two replicating approaches and to test research questions associated with the third area of investigation.

As explained in Section 3.2.4 the benchmarks for the replication are HFR non-investable (HFRI) and investable (HFRX) style indices as well as TASS indices. The main focus is on clones of HFR indices because HFR indices in contrast to TASS indices are not used in the first part of this study for model selection; hence, they provide an additional robustness check of the findings on nonlinearities.

To evaluate and compare tracking accuracy of linear and nonlinear replicating portfolios of investable (HFRX) and non-investable (HFRI) hedge fund style indices several measures and statistical tests are proposed.

Firstly, the mean and median value of the difference of returns ΔR of (i) HFRX and HFRI indices, (ii) HFRI and its linear replicating portfolio, (iii) HFRI and its nonlinear replicating portfolio, (iv) HFRX and its linear replicating portfolios and (v) HFRX and its nonlinear replicating portfolio are calculated. To test statistical significance of the difference between the returns the two-sided heteroscedastic t-test and nonparametric Wilcoxon signed-rank test are performed and their p-values calculated. The less is the value of ΔR, the less is the average deviation of the replicating portfolio from its benchmark.

Secondly, several other commonly used tracking statistics are estimated: the annualized tracking error (TE) (also known as root mean square error, RMSE), the mean absolute error (MAE), the annualized geometric average excess return (AER) and the cumulative geometric excess return over the whole period (CER). The formulas for these measures are given below:

$$TE = \sqrt{\frac{12}{T}\sum_{t=1}^{T}(\hat{r}_t - r_t)^2} \quad \textbf{(5.43)}$$

$$MAE = \frac{\sum_{t=1}^{T}|\hat{r}_t - r_t|}{T} \quad \textbf{(5.44)}$$

$$AER = \left[\prod_{t=1}^{T}(1 + \hat{r}_t - r_t)\right]^{\frac{12}{T}} - 1 \quad \textbf{(5.45)}$$

$$CER = \prod_{t=1}^{T}(1 + \hat{r}_t - r_t) - 1 \quad \textbf{(5.46)}$$

where $\hat{r}_t$ is the return of the replicating strategy, r_t is the return of the benchmark, T is the number of observations.

The TE and the MAE are two alternative measures of the tracking accuracy. Comparing between them the TE gives more weight to points further away from the mean than the MAE, therefore it can be less robust to influence of outliers in some cases.

The other two measures, the AER and the CER, compliment the analysis as they show whether the replicating portfolio under- or overperforms the benchmark. The TE and the

MAE are always positive and if the fit is not perfect then they do not allow gauging of the relative performance of the clone against the benchmark, which is also important for investors. The AER is an average annual relative performance measure, while the CER measures cumulative deviation of the clone from the benchmark. A good replicating portfolio has low tracking error and low mean absolute error; also, positive values of the AER and the CER are preferred for investors, ceteris paribus.

Thirdly, to evaluate the performance characteristics of indices and replicating portfolios following performance metrics are analysed: the annualized Sharpe ratio (Sharpe)[89], the modified Sharpe ratio (modified Sharpe), the Sortino ratio (Sortino), the information ratio (IR) and the expected shortfall (ES):

$$Sharpe = \frac{E(r_t)}{\sigma(r_t)} \tag{5.47}$$

$$Modified\ Sharpe = \frac{E(r_t)}{MVaR(r_t)} \tag{5.48}$$

$$Sortino = \frac{E(r_t)}{\delta(r_t)} \tag{5.49}$$

$$IR = \frac{E(\hat{r}_t - r_t)}{\sigma(\hat{r}_t - r_t)} \tag{5.50}$$

$$ES = \frac{1}{\alpha}\int_0^{\alpha} VaR_{\gamma}(r_t)d\gamma \tag{5.51}$$

where $E(r_t)$ is the annualized expected return and $\sigma(r_t)$ is the annualized standard deviation of returns; $MVaR(r_t)$ is the modified value at risk (Favre & Galeano, 2002b); $\delta(r_t)$

[89] See the comment on the Sharpe ratio in footnote 87

is the downside deviation[90]; $E(\hat{r}_t - r_t)$ and $\sigma(\hat{r}_t - r_t)$ are the expected excess return of replicating portfolio over the benchmark and its standard deviation respectively.

The Sharpe ratio as explained in Section 5.2.2 is a standard risk-adjusted return measure. Its downside is that it relies on the standard deviation as a risk measure and therefore ignores higher order moments and the tail risk of the return distribution. Higher order moments and the tail risk are particularly important in hedge funds context, because hedge funds are known to have asymmetric and non-normal risk-return profiles. Among a number of risk-adjusted measures which surmount this drawback are the modified Sharpe ratio and the Sortino ratio. The modified Sharpe ratio (Gregoriou & Gueyie, 2003) corrects for the skewness and the excess kurtosis of the return distribution by using the Cornish-Fisher modified VaR as a measure of risk[91] instead of the standard deviation. The Sortino ratio (Sortino & Price, 1994) adjusts for the asymmetry of returns by penalizing only those returns which fall below a specified target (e.g. 0%), while the Sharpe ratio penalizes both the upside and the downside volatility equally. The higher is the Sharpe ratio, the modified Sharpe ratio and the Sortino ratio, the better is the risk-adjusted performance of the portfolio.

The information ratio, also known as appraisal ratio, is a measure of performance relative to some benchmark, as opposed to the Sharpe and the Sortino ratios, which measure absolute

[90] The downside deviation is a measure of the downside risk that focuses on returns that fall below the minimum threshold or the minimum acceptable return (MAR). Here the MAR is assumed to be zero; thus, the downside deviation is equivalent to the standard deviation of returns below zero.

[91] The Value at risk (VaR) is defined as the high quantile (e.g. a 95% quantile) of the negative value of the returns. Therefore, to calculate the VaR a quantile of the return distribution needs to be estimated. The traditional approach is to make a distributional assumption, e.g. the Gaussian distribution, or to utilize an empirical quantile. When the distribution is known to be non-normal, one may choose to adjust the traditional gaussian VaR for the skewness and the kurtosis of the distribution by using the Cornish-Fisher expansion. The Cornish-Fisher estimate of the VaR is called the modified VaR (Favre & Galeano, 2002b).

performance. It is defined as the ratio of the expected active return (the excess return over benchmark) to the volatility of active return (volatility of the tracking error). It helps to gauge how consistent the performance of the replicating portfolio is relatively to its benchmark. In other words, it may help to identify if a clone beats the benchmark by a high margin in only a few months or by a low margin every month. The higher is the information ratio the more consistent is the relative performance of the replicating portfolios. A high ratio means that a clone achieves higher returns more efficiently than one with a low ratio by increasing the tracking error. The expected shortfall (ES) has been discussed in Section 5.2.2.

Chapter 6 Results – Modeling and Assessing Nonlinearities in Hedge Fund Indices

This chapter presents the results concerning modeling and assessment of nonlinearities in hedge fund portfolios. The main focus is on statistical analysis of the evidence of nonlinear risk exposures in hedge fund portfolios and selection of a suitable nonparametric model from the range of models proposed in Chapter 5. Section 6.1 begins with descriptive statistics of TASS hedge fund indices and three groups of risk factors proposed in Section 4.4. Section 6.2 thoroughly examines the evidence of hedge funds' nonlinear exposures to systematic risk factors. Section 6.3 presents the results of an in-sample analysis of linear and nonparametric models, while Section 6.4 discusses the results of an out-of-sample test of models' performance. Section 6.5 makes concluding remarks.

6.1 Descriptive Statistics of TASS Indices

Table 6.1 presents summary statistics for TASS hedge fund style indices including the Hedge Fund Composite Index from January 1994 to September 2010. Several observations can be drawn from the table. Firstly, raw returns of the indices in all the styles except one are positive. The Sharpe ratio of most of the style indices is above 0.5 and in five styles (CA, ED, GM, LSE, MS) as well as for the composite index (HFC) it is above one. For comparison the

Sharpe ratio of the S&P 500 total return index for the same period is 0.4892. Thus, most of the hedge fund styles with the exception of the Dedicated Short Bias category have demonstrated good risk-adjusted performance relatively to the market index during this sixteen-year period. The Global Macro style has demonstrated the highest average annual return of 12.4% among all the styles and the Event Driven style has been the best in terms of the risk-adjusted performance; its average annual Sharpe ratio is 1.667. Secondly, in line with the earlier literature (Malkiel & Saha, 2005)hedge funds exhibit non-normal and mostly negatively skewed patterns of return distributions. Nine out of twelve indices are negatively skewed and eight have positive excess kurtosis[93]. The Jarque–Bera test on normality is rejected at 1% level in all the styles except the Managed Futures category. Fat-tailed and leptokurtic returns distributions of most of hedge fund strategies have been documented earlier by Lo (2001) and Malkiel and Saha (2005). The Managed Futures style, which aggregates Commodity Trading Advisors (CTAs) and Commodity Pool Operators (CPOs), is the only style known to have slightly positive skewness of the return distribution (Do et al., 2014, forthcoming; Dori, Krieger, & Schubiger, 2013; Fung & Hsieh, 2001; Kat, 2004). Non-normality of return distributions provides empirical confirmation to theoretical arguments put forward in Section 3.1.2 that standard asset pricing models and linear multi-factors models might be biased because the key assumption of normality is violated.

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[92] Author's calculation

[93] The normal distribution has kurtosis of 3

Table 6.1 Descriptive Statistics of Hedge Fund Style Returns

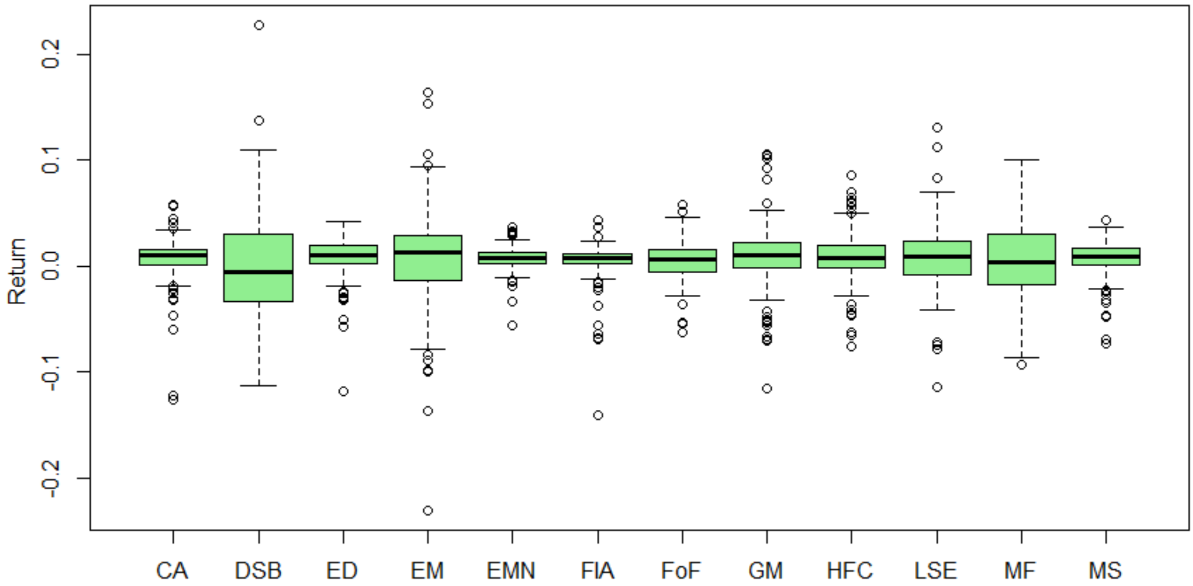
The table presents descriptive statistics for TASS hedge fund indices from January 1994 to September 2010: annualized geometric mean, annualized standard deviation, annualized Sharpe ratio (Sharpe Ratio), skewness (Skew), kurtosis, minimum, maximum and the Jarque-Bera test statistic (JB). Superscripts *, ** and *** near JB test statistic indicate the statistical significance at 10%, 5% and 1% levels, respectively. The styles are: Convertible Arbitrage (CA), Dedicated Short Bias (DSB), Emerging Markets (EM), Equity Market Neutral (EMN), Event Driven (ED), Fixed Income Arbitrage (FIA), Global Macro (GM), Long-Short Equity (LSE), Managed Futures (MF), Multi-Strategy (MS), Fund of Funds (FoF), Hedge Fund Composite (HFC).

Hedge Fund Strategy	No. of Obs.	Annualized Mean	Annualized SD	Sharpe Ratio	Skew	Kurtosis	Minimum	Maximum	JB
CA	201	0.078	0.071	1.093	-2.724	15.54	-0.126	0.058	2271.044***
DSB	201	-0.032	0.171	-0.185	0.673	1.433	-0.113	0.227	32.366***
EM	201	0.081	0.153	0.531	-0.768	4.777	-0.23	0.164	210.910***
EMN	201	0.052	0.107	0.483	-11.722	152.758	-0.405	0.037	200032.895***
ED	201	0.102	0.061	1.667	-2.471	13.134	-0.118	0.042	1649.260***
FIA	201	0.052	0.060	0.868	-4.249	27.788	-0.14	0.043	7071.633***
GM	201	0.124	0.101	1.231	-0.026	3.384	-0.116	0.106	95.920***
LSE	201	0.100	0.100	1.000	0.004	3.311	-0.114	0.130	91.826***
MF	201	0.064	0.117	0.545	0.014	0.044	-0.094	0.100	0.023
MS	198	0.081	0.055	1.478	-1.749	5.983	-0.073	0.043	396.211***
FoF	201	0.058	0.059	0.985	-0.501	2.075	-0.063	0.058	44.472***
HFC	201	0.093	0.077	1.198	-0.208	2.367	-0.075	0.085	48.384***

To gain a deeper insight into the distributional properties of hedge fund style returns, Figure 6.1 shows the box plots of style returns. Box plots display the degree of dispersion (spread) and skewness in the data, and help identifying outliers. Overall, the graph confirms negatively skewed pattern of returns, since most of the distributions have a heavy tail on the negative side. Importantly, the non-normal properties of return distributions cannot be attributed to a small number of outliers; rather they represent a genuine feature of hedge funds' return distributions. Only the distribution in the Managed Futures style does not exhibit such pattern.

Figure 6.1 Return Distributions of Hedge Fund Styles

The figure demonstrates box plots of hedge fund style return distributions. The bottom and upper edge of each box represent the first and the third quartiles of the return distribution; the solid line inside the box is the median return; the whiskers outside the box limit the range of returns which fall into 1.5 times the interquartile range; the black circles outside the whiskers depict potential outlier points.



The next Table 6.2 provides summary statistics of three sets of risk factors: the seven factors of Fung and Hsieh (2004b) (FH7), the six factors of Hasanhodzic and Lo (2007) (HL6) and of the other eight factors as described in Section 4.4. As seen from the table most of the factors have non-normal distributions as indicated by the Jarque–Bera test statistics. This is a common finding for most financial time-series variables. Another interesting observation is related to Fung and Hsieh's (2004b) trend-following factors. Annualized geometric mean for all PTFS factors is negative and close or below -15%. On the other hand, the mean return of the Managed Futures style for the same period is positive 6.4% (see Table 6.1). Given that trend-following strategy is considered to be the dominant strategy of the Managed Futures style (Fung & Hsieh, 2001) and PTFS factors are designed to replicate the risk-return profile of trend-following funds, the discrepancy is noteworthy.

Table 6.2 Descriptive Statistics of Risk Factors

The table presents descriptive statistics for risk factors from January 1994 to September 2010: annualized geometric mean (Mean), annualized standard deviation (SD), skewness (Skew), kurtosis, minimum, maximum and the Jarque-Bera test statistic (JB). Superscripts *, ** and *** near JB statistic figures indicate the statistical significance at 10%, 5% and 1% levels, respectively. For variable definitions see Table 4.5.

Risk Factor	Mean	SD	Skew	Kurtosis	Minimum	Maximum	JB
				FH7 factors			
SNPMRF	0.040	0.157	-0.675	0.880	-0.169	0.096	21.739***
SCMLC	-0.001	0.122	0.280	4.531	-0.164	0.184	174.577***
T10Y	0.753	0.041	0.114	-0.623	0.020	0.078	3.688
CREDSPR	0.356	0.036	0.231	-0.234	-0.001	0.058	2.248
PTFSBD	-0.258	0.521	1.417	2.746	-0.250	0.690	130.414***
PTFSFX	-0.183	0.676	1.385	2.731	-0.300	0.900	126.716***
PTFSCOM	-0.149	0.481	1.278	2.575	-0.230	0.650	110.212***
				HL6 factors			
SP500	0.075	0.157	-0.702	0.904	-0.168	0.098	23.335***
USD	-0.013	0.082	0.276	0.789	-0.063	0.088	7.768**
BOND	0.063	0.043	-0.577	4.408	-0.060	0.054	173.875***
CREDIT	-0.001	0.079	-0.160	6.118	-0.110	0.099	314.298***
GSCI	0.045	0.227	-0.387	1.434	-0.282	0.197	22.222***
DVIX	0.043	0.655	1.260	2.973	-0.327	0.908	127.184***
				Additional factors			
SMB	0.019	0.128	0.849	7.570	-0.167	0.222	504.121***
HML	0.026	0.122	0.003	2.454	-0.128	0.138	50.444***
UMD	0.037	0.197	-1.540	9.008	-0.347	0.184	758.980***
EQINT	0.053	0.168	-0.686	1.629	-0.202	0.130	37.970***
EQEM	0.067	0.246	-0.759	1.818	-0.289	0.171	46.992***
HYIELD	0.074	0.095	-1.139	8.806	-0.159	0.121	692.877***
BONDINT	0.065	0.085	0.264	0.475	-0.057	0.089	4.217
BONDCNV	0.075	0.133	-0.988	4.061	-0.180	0.135	170.820***

Table 6.3 gives correlation coefficients with associated p-values between hedge fund style returns and risk factors. Holm-Bonferroni adjustment (Holm, 1979) is applied to all p-values. The adjustment counteracts the problem of testing multiple hypotheses using the same data and provides more conservative estimates of the p-values. All the styles except the Managed Futures category have statistically significant correlation with equity markets in the US (SNPMRF and SP500), emerging markets (EQEM) and in the world (EQINT). Half of the styles show significant correlation with the Fama and French's (1993) size (SMB) and value factors (HML). Conversely, none of the styles are significantly correlated with Carhart's

(1997) momentum factor (UMD), consistent with evidence in Capocci and Hubner (2004). Other factors correlated with most of the styles include the credit spread variable, particularly in relative value or arbitrage styles (CA, FIA, ED), commodities, volatility, high yield bonds and convertible bonds. Correlation coefficients of hedge fund style returns with the trend following factors are relatively low and below 0.2, with the exception of the Managed Futures style where correlations are around 0.3 and statistically significant. Overall, these results confirm that hedge fund strategies are hardly market neutral, because most of them are correlated with various risk factors.

Table 6.3 Correlation of Hedge Fund Indices and Risk Factors

The table shows correlations between TASS hedge fund indices and three sets of risk factors. Correlations significant at the Holm-Bonferroni-adjusted significance level of 5% are shown in bold type.

Hedge Fund Strategy	**CA**	**DSB**	**EM**	**EMN**	**ED**	**FIA**	**GM**	**LSE**	**MF**	**MS**	**FoF**	**HFC**
FH factors												
SNPMRF	**0.36**	**-0.75**	**0.54**	**0.27**	**0.62**	**0.34**	**0.24**	**0.64**	-0.11	**0.35**	**0.56**	**0.55**
SCMLC	0.13	**-0.37**	**0.24**	0.09	**0.28**	0.10	0.05	**0.41**	-0.01	0.15	**0.33**	**0.27**
T10Y	0.05	0.01	0.03	0.13	0.11	0.05	-0.01	0.11	-0.06	0.08	0.12	0.08
CREDSPR	-0.05	0.06	-0.10	**-0.24**	**-0.22**	-0.11	0.02	-0.18	0.04	-0.18	**-0.19**	-0.14
PTFSBD	**-0.21**	0.18	**-0.25**	-0.18	**-0.36**	**-0.22**	-0.12	**-0.21**	**0.26**	-0.16	**-0.20**	**-0.25**
PTFSFX	**-0.25**	0.09	-0.17	0.05	-0.14	**-0.30**	0.03	-0.07	**0.33**	-0.09	-0.02	-0.04
PTFSCOM	-0.19	0.04	-0.09	0.06	-0.10	-0.14	0.05	-0.04	**0.28**	-0.07	0.01	0.01
HL factors												
SP500	**0.36**	**-0.75**	**0.53**	**0.28**	**0.62**	**0.34**	**0.25**	**0.65**	-0.11	**0.35**	**0.56**	**0.56**
USD	-0.13	0.10	-0.07	-0.10	-0.11	-0.19	0.08	**-0.21**	-0.20	**-0.28**	-0.15	-0.05
BOND	**0.32**	0.00	0.09	-0.07	0.12	**0.26**	**0.31**	**0.19**	0.19	0.16	**0.19**	**0.25**
CREDIT	**0.63**	**-0.43**	**0.43**	**0.30**	**0.58**	**0.53**	0.12	**0.42**	-0.19	**0.57**	**0.45**	**0.41**
GSCI	**0.31**	-0.14	**0.26**	**0.26**	**0.35**	**0.39**	0.18	**0.35**	0.18	**0.37**	**0.40**	**0.34**
DVIX	**-0.32**	**0.50**	**-0.41**	-0.05	**-0.48**	**-0.24**	**-0.22**	**-0.48**	0.06	**-0.25**	**-0.40**	**-0.42**
Additional factors												
SMB	0.15	**-0.42**	**0.30**	0.08	**0.31**	0.09	0.08	**0.46**	-0.04	0.16	**0.39**	**0.32**
HML	0.01	**0.36**	**-0.23**	0.10	-0.11	0.10	-0.06	**-0.43**	0.08	-0.01	**-0.27**	**-0.24**
UMD	-0.17	0.17	-0.04	-0.13	-0.08	-0.13	0.14	0.17	0.19	-0.08	0.11	0.13
EQINT	**0.41**	**-0.63**	**0.59**	**0.24**	**0.64**	**0.40**	0.20	**0.66**	0.00	**0.46**	**0.62**	**0.55**
EQEM	**0.42**	**-0.65**	**0.80**	**0.21**	**0.68**	**0.40**	**0.28**	**0.67**	-0.02	**0.34**	**0.71**	**0.61**
HYIELD	**0.65**	**-0.49**	**0.46**	**0.36**	**0.62**	**0.61**	**0.23**	**0.48**	-0.15	**0.56**	**0.50**	**0.50**
BONDINT	-0.02	-0.02	-0.06	0.00	-0.05	-0.01	-0.09	0.09	**0.27**	0.11	0.04	-0.05
BONDCNV	**0.58**	**-0.76**	**0.64**	**0.26**	**0.73**	**0.50**	**0.35**	**0.84**	-0.07	**0.51**	**0.76**	**0.73**

Table 6.4 reports correlation matrix for the risk variables. Correlations within the FH7 and HL6 sets are not high except for T10Y and CREDSPR variables with correlation of -0.68 and SP500 and DVIX variables with correlation of -0.64. Among the additional eight variables particularly high are correlations between three equity market variables (SP500, EQINT, EQEM) and equity variables and convertible bond variable (above 0.7). Convertible bonds have features of both fixed income securities and equity. They offer investors downside protection during times when share price declines in the form of fixed interest payments, while allowing to participate in upside stock movements by exercising the conversion option. Since rising equity market environment dominated the period of observation in 1994-2010 it is not surpiring that convetible bonds behave more like equity. This explains their high correlation with equity. In general, high correlations bewtween some variables in the extended set should not pose a series problem in the analysis, because variable selection procedures to identify most important variables are applied in all cases when additional factors are used in the models.

Table 6.4 Variables Correlation

	SNPMRF	SCMLC	T10Y	CREDSPR	PTFSBD	PTFSFX	PTFSCOM	SP500	USD	BOND	CREDIT	GSCI	DVIX	SMB	HML	UMD	EQINT	EQEM	HYIELD	BONDINT	BONDCNV	USTB3MNT
SNPMRF		0.04	0.12	-0.21	-0.19	-0.18	-0.13	1.00	-0.20	0.14	0.53	0.21	-0.65	0.07	-0.18	-0.33	0.82	0.74	0.61	0.08	0.83	0.06
SCMLC			-0.07	0.02	-0.09	0.00	-0.04	0.03	-0.11	-0.10	0.24	0.15	-0.14	0.93	-0.16	0.08	0.18	0.25	0.25	-0.02	0.36	-0.12
T10Y				-0.68	0.12	-0.07	-0.04	0.15	0.08	-0.07	0.03	0.05	0.00	-0.04	-0.05	0.06	0.07	-0.02	-0.02	-0.10	0.09	0.70
CREDSPR					0.00	0.08	0.00	-0.22	-0.03	0.15	-0.06	-0.12	0.00	0.03	0.04	-0.05	-0.21	-0.13	-0.08	0.10	-0.16	-0.42
PTFSBD						0.23	0.19	-0.19	-0.07	0.07	-0.26	-0.05	0.25	-0.06	-0.06	-0.01	-0.19	-0.21	-0.23	0.18	-0.18	0.01
PTFSFX							0.38	-0.18	-0.07	0.01	-0.26	-0.06	0.20	-0.01	0.02	0.12	-0.16	-0.17	-0.23	0.25	-0.18	-0.01
PTFSCOM								-0.13	-0.03	0.01	-0.17	0.05	0.08	-0.04	-0.02	0.21	-0.08	-0.13	-0.20	0.12	-0.13	0.00
SP500									-0.19	0.14	0.52	0.21	-0.64	0.07	-0.17	-0.32	0.82	0.73	0.60	0.08	0.82	0.10
USD										-0.27	-0.17	-0.34	0.07	-0.06	-0.05	0.06	-0.46	-0.26	-0.24	-0.86	-0.24	0.09
BOND											0.08	0.08	-0.21	-0.11	0.06	-0.02	0.15	0.10	0.34	0.43	0.23	0.04
CREDIT												0.22	-0.47	0.25	-0.08	-0.36	0.58	0.58	0.80	-0.07	0.64	-0.11
GSCI													-0.18	0.12	0.01	0.08	0.34	0.33	0.23	0.17	0.31	0.05
DVIX														-0.15	0.17	0.15	-0.57	-0.57	-0.46	0.05	-0.60	0.06
SMB															-0.37	0.09	0.19	0.28	0.25	-0.05	0.41	-0.12
HML																-0.16	-0.13	-0.22	-0.02	0.05	-0.37	0.03
UMD																	-0.26	-0.27	-0.40	-0.04	-0.19	0.14
EQINT																		0.80	0.62	0.29	0.78	-0.01
EQEM																			0.62	0.09	0.76	-0.10
HYIELD																				0.10	0.73	-0.10
BONDINT																					0.10	-0.08
BONDCNV																						0.02

6.2 Evidence on Nonlinearities

It is known in statistics that the correlation coefficient measures only a linear dependence between variables. If the relationship is nonlinear, e.g. concave or convex, rather than linear, the correlation might significantly underestimate the relationship between the two variables. Consider a classical textbook example when there is a direct link between the two variables but the correlation is zero. Let X be a random variable with a standard normal distribution $N(0,1)$ and Y be a random variable such that $Y = X^2$. As can be easily demonstrated the correlation coefficient between X and Y is equal to zero, even though there is a clear deterministic relationship between the two variables:

$$cor(X,Y) = \frac{cov(X,Y)}{\sqrt{Var(X)}\cdot\sqrt{Var(Y)}} = \frac{E(X\cdot X^2) - E(X)\cdot E(X^2)}{\sqrt{E(X^2) - (E(X))^2}\cdot\sqrt{E(X^4) - (E(X^2))^2}}$$

$$= \frac{0 - 0\cdot 1}{\sqrt{1-0}\cdot\sqrt{3-1}} = 0$$

The reason for this paradox is that the relationship between the variables is quadratic, rather than linear and the correlation fails to capture it.

This example illustrates that relying exclusively on the correlation coefficient to judge the relationship between variables can be misleading. Continuing the example above, a simple way to detect that variables X and Y are related in a more complex is to calculate the correlation between the squared value of the first variable X and the second variable Y, i.e. $cor(X^2, Y)$. This correlation immediately reveals a perfect quadratic link between the two variables: $cor(X^2, Y) = cor(X^2, X^2) = 1$. More generally, the correlation of the form $cor(X^n, Y), n > 1$ (or $cor(X, Y^m), m > 1$) can be defined as the higher order or the nonlinear correlation coefficient.

In Figure 6.2 the idea of the higher order correlation is applied to verify higher order dependence between the risk variables and hedge fund returns. It presents absolute values of correlation coefficients between hedge fund style returns and the second and the third powers of HL6 variables and the other eight variables. Values of higher order correlations which exceed linear correlation coefficients might indicate a nonlinear relationship between hedge fund returns and the risk factors.

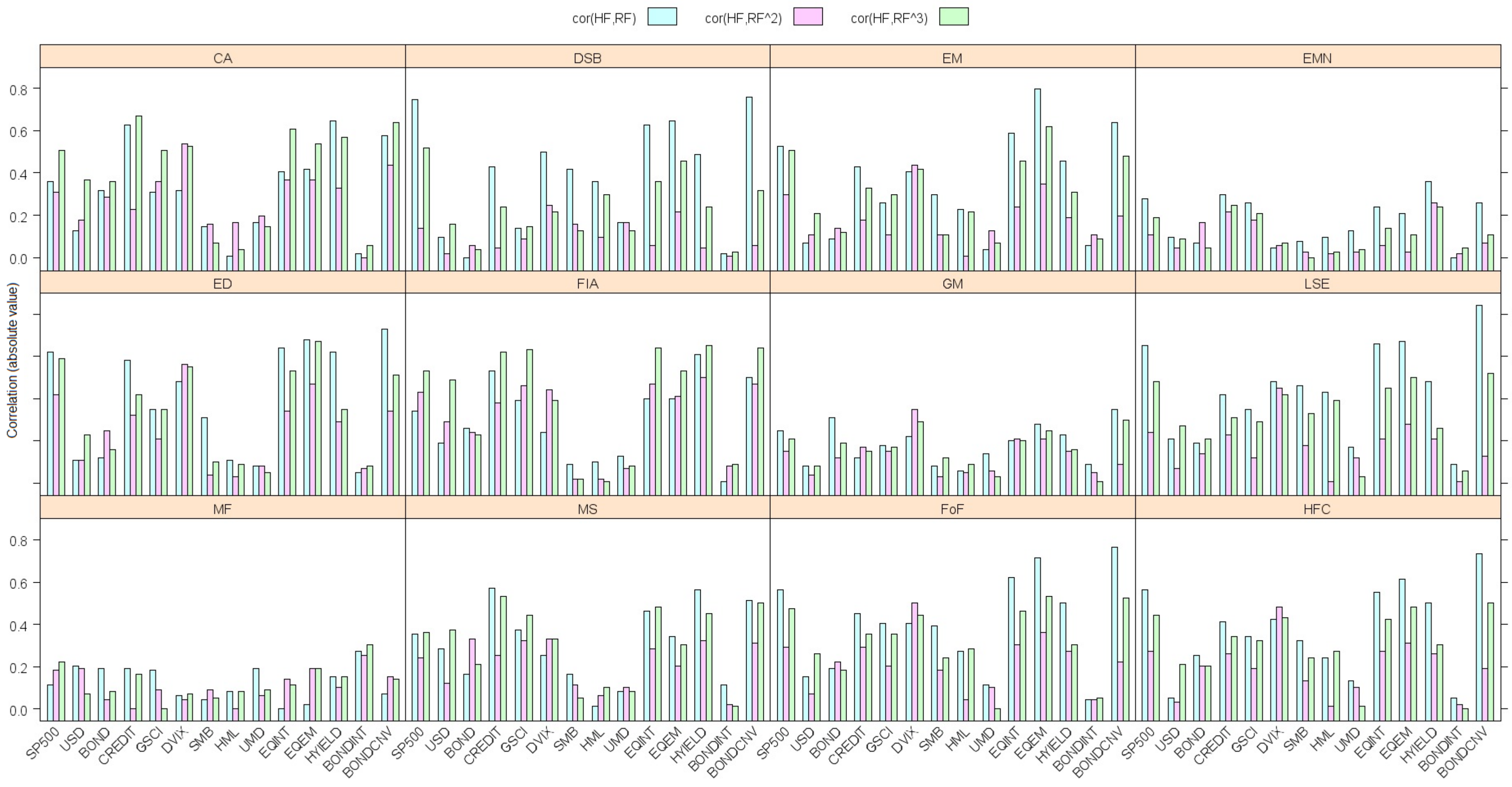
It is apparent from Figure 6.2 that every hedge fund style has at least one risk factor with the higher order correlation coefficient exceeding the linear correlation coefficient. At the same time the non-directional styles exhibit more nonlinear correlations than the directional styles. For instance, none of the higher order correlations in the Long Short Equity and the Dedicated Short Bias styles exceed the linear correlation (except for the USD variable). Conversely, most of the nonlinear correlation coefficients in the Convertible Arbitrage and the Fixed Income Arbitrage styles are above the values of the linear correlation. This finding suggests that the likelihood of nonlinear relationships in arbitrage related styles is higher than in the directional styles. A similar pattern is observed in the Managed Futures style. While linear correlations with three equity factors are very weak and not statistically different from zero[94] (0.00 with EQINT, -0.02 with EQEM and -0.11 with SP500), the second order correlations are positive and statistically significant (0.14, 0.19 and 0.18 respectively). This finding is consistent with Fung and Hsieh (2001) who document a nonlinear convex relationship between the returns of trend following hedge funds and world equity returns, because positive second order correlation coefficient is equivalent to a

[94] Statistical significance is not given in Figure 6.2, but it is available in additional results upon request.

convex pattern of the relationship. In summary, Figure 6.2 provides strong preliminary evidence of nonlinear risk in some of hedge fund categories.

Figure 6.2 Higher Order Correlations Between Hedge Fund Indices and Risk Factors

The figure presents the absolute values of correlation coefficients between hedge fund style returns and the first, second and third powers of risk factors' returns, i.e. $cor(HF\ style, Risk\ Factor)$, $cor(HF\ style, Risk\ Factor^2)$, and $cor(HF\ style, Risk\ Factor^3)$. The factors include HL6 variables and an additional set of 8 variables.



To provide further corroborating evidence of nonlinearities as well as to see potential patterns of risk exposures Figure 6.3 demonstrates scatterplots of returns of hedge fund styles and the risk factors. Loess curves are also fitted for every graph to visualize the relationship. P-values of the Ramsey (1969) RESET test are reported at the top of the graphs and complement graphical analysis. RESET test is a general specification test for the linear regression model. It tests whether higher order combinations of predictors help explaining the response variable[95].

As seen from the graphs patterns of risk exposures vary greatly across the styles. In some styles exposures are mainly linear, while in others nonlinear patterns dominate. Nevertheless, there are several groups of hedge fund styles which share similar characteristics akin to the findings in Fung and Hsieh (1999).

Arbitrage Styles

The first group comprises funds which take advantage of arbitrage opportunities arising due to pricing discrepancies between related securities or temporary market inefficiencies. It includes the Convertible Arbitrage, the Fixed Income Arbitrage and the Event Driven styles. The group shows very clear and highly statistically significant at 1% level nonlinear patters in most of the risk factors. Of particular interest are exposures to equity (SP500, EQINT, EQEM), bonds (BOND, BONDCNV) and credit (CREDIT, HYIELD) related variables. The profile of the relationship between style returns and the factors in many cases resembles a payoff of a short put option position. As explained in Section 3.1.1 arbitrage traders essentially write a put option or sell financial insurance to other market participants against adverse events or specific type of financial risk. For instance, funds in the Event Driven category take the risk

[95] Terms up to the third power are used in RESET test displayed in Figure 6.3

of non-realization of certain events, such as mergers, takeovers, and company reorganizations (Mitchell & Pulvino, 2001). The risk is higher during equity market downturns and therefore leads to larger losses; conversely, when markets are up, a larger proportion of deals go through and the event arbitrageurs make profits; however, the profits are unrelated to the extent to which the market goes up.

Similar reasoning can be applied to explain the short put-like exposure of the Fixed Income Arbitrage style to equities, bonds and credit related variables. Fixed income funds are exposed to a 'sudden event' risk when interest rates move sharply, credit spreads widen, and liquidity dries up. Hence, they earn small positive returns most of the time, but experience large losses during financial markets turmoil[96]. The fixed income arbitrage style and event driven funds are often referred to as 'short volatility' strategies (Anson & Ho, 2003; Fung & Hsieh, 1999; Jaeger, 2008). Indeed, the exposure of arbitrage styles to volatility (DVIX) in Figure 6.3 partially resembles a short position in market volatility. Funds suffer losses when market volatility is very high but earn positive returns when i is low. However, as graphs suggest the effect is more like the payoff of a short call option position, because decrease in volatility after a certain point no longer has an accelerating positive impact on profitability of the funds.

Convertible arbitrage funds like event driven and fixed income arbitrage funds also exhibit nonlinear risk-return relationships with respect to equity, bond, credit and volatility variables. These funds lose money during large down moves in the markets.

[96] The most notorious example is the collapse of Long-Term Capital Management in 1998, one of the largest fixed income arbitrage funds. It lost $1.6 billion in swap spread positions before its collapse (Lowenstein, 2000). At core of LTCM's strategies were yield spread and swap spread arbitrage strategies. See Perold (1999) for details.

Overall the profiles of risk exposures of arbitrage styles generally confirm nonlinear patterns documented earlier in the literature.

Directional Styles

This group includes the Long-Short Equity, the Dedicated Short Bias and the Emerging Markets styles. Fund managers belonging to these categories implement in trading strategies their views on the future direction of the markets and thus have net long or short market exposure. The focus market for the Long-Short Equity and the Dedicated Short Bias styles is equity, while funds from the Emerging Market style focus on emerging markets equity and to a lesser extent emerging markets bonds[97]. From Figure 6.3 it can be concluded that risk exposures of directional styles in their dominant markets are mostly linear; the RESET test does not support the hypothesis of nonlinearities in risk exposures to focus markets at 5% level. This is consistent with other studies which do not find any nonlinearities among these styles (Agarwal & Naik, 2004; Diez de los Rios & Garcia, 2011; Fung & Hsieh, 2004a). For instance, Fung and Hsieh (2004a) argues that the Long-Short Equity category has only two primary linear risk exposures – equity market risk and the size spread (i.e. the difference between small and large capitalized stocks); the authors also do not find any evidence of market timing in aggregate returns of long-short equity funds. One of the reasons of mostly linear exposures of emerging market funds in their dominant markets is due to restrictions on short selling and lack of availability of derivative instruments in emerging markets; hence, emerging markets funds are bound to investing in traditional assets which have linear payoffs (Eling & Faust, 2010).

[97] Eling and Faust (2010) report that the correlation of the Emerging Market style returns with emerging markets bond returns was declining, while the correlation with equities was increasing in the last decade. After the recent financial crisis the correlation with bonds dropped to below 0.2 level and the correlation with equities increased to above 0.9 level.

Although the exposures to focus markets of directional styles are mostly linear, there are some asymmetric effects related to other variables. For instance, the Emerging Markets style exhibit a nonlinear exposure to the US equity and the Dedicated Short Bias style has a nonlinear exposure to convertible bonds variable. Although these nonlinearities are statistically significant, they are likely to reflect complex nonlinear relationships between the variables themselves, rather than be a genuine source of economic risk for hedge funds. As the two graphs in Figure 6.4 illustrate, the correlations between the S&P500 index (SP500) and the MSCI Emerging Markets Index (EQEM) and between the S&P500 index and the Merrill Lynch All US Convertibles Index (BONDCNV) are nonlinear and statistically significant at 5% level. As a result, due to the effect of concurvity[98] between the factors some nonlinear patterns may appear where they are not expected, i.e. in the markets where funds are not trading actively. This is because Figure 6.3 displays bivariate scatter plots; each plot is constructed independently from the others. When modeling hedge fund returns using a GAM, the backfitting algorithm that fits the model takes into account the effect of all the variables simultaneously.

Managed Futures/CTAs

The risk exposures of this style to equities, currency and commodities exhibit a nonlinear behaviour, though the RESET test rejects the linear specification form at 5% level only for emerging markets equity variable. Given that a large faction of CTA managers employ trend-following strategies in equity, currency and commodity markets these nonlinear patterns are expected. The exposure to international and emerging market equity variables resemble

[98] Concurvity can be viewed as a generalization of the concept of correlation and the issue of multicollinearity in the regression framework. In simple terms it refers to the dependence between functional forms of two variables.

the payoff of a straddle. Such payoff can be an indication of market timing ability among the CTA managers, though the graphs alone are clearly not enough to verify it. Nevertheless, there is some support in the literature to this conjecture. Diez de los Rios and Garcia (2011) observes similar straddle-like payoff using a piecewise linear regression while Kazemi and Li (2009) document that CTAs overall exhibit market return timing and volatility timing ability.

Equity Market Neutral

This style does not exhibit any statistically significant nonlinear risk exposures with the exception of the currency variable. Linear correlations with different market variables as reported earlier in Table 6.3 are also low. Thus, weak evidence of any linear or nonlinear risk exposures confirms market neutrality of the aggregate portfolio of equity market neutral funds. However, this does not mean market neutrality of all individual funds in the portfolio, as aggregation may neutralize opposite risk exposures.

Global Macro

The Global Macro style demonstrates asymmetric risk exposures to currency risk and volatility shifts. The exposure to the US currency fluctuations resembles a payoff of a collar option strategy, while exposure to volatility is akin to a short call option position. The latter pattern is similar to concave form of the exposure documented in Giannikis and Vrontos (2011).

Multi-Focus

There is a strong evidence of nonlinear risk in the Multi-Strategy and the Fund of Funds categories. Nonlinearities are observed in most of the risk exposures and particularly to bonds, equities, commodities and credit variables. Exposures of both styles look very similar.

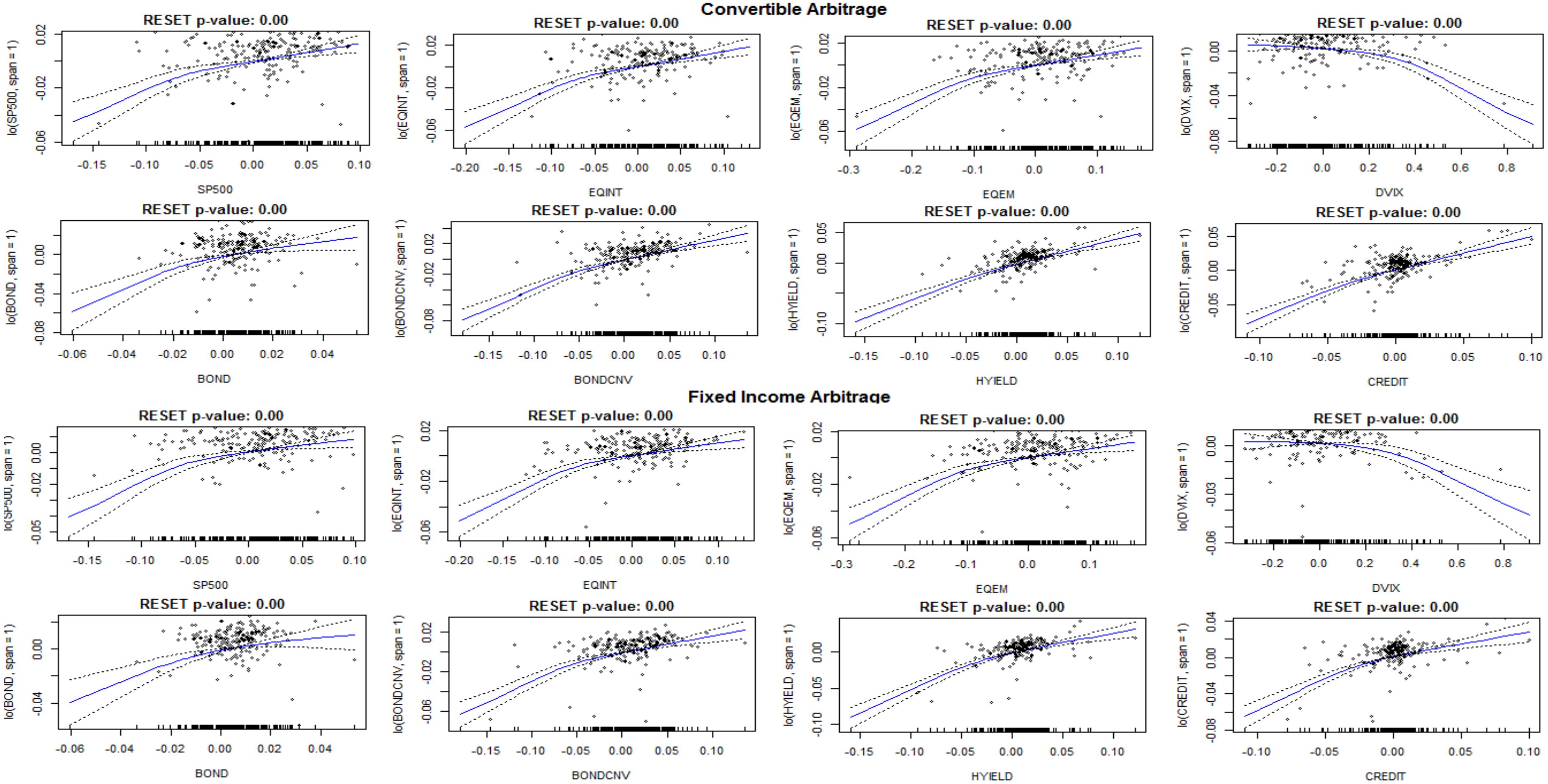
The diverse profile of risk exposures is explained by focus on multiple markets of these funds. Both styles have the ability to reallocate capital between different hedge fund strategies in response to changing market conditions. The absence of the primary trading strategy makes economic interpretation of risk profiles of these styles difficult.

Summarizing this section, higher order correlation analysis, loess scatter smoother graphs and the RESET test for linear specification provide convincing evidence of nonlinear effects in risk exposures of some categories of hedge funds. The nonlinear risk is more pronounced in arbitrage styles and styles following multiple strategies and is weaker in directional styles. Given this motivation the next section examines a range of nonparametric hedge fund pricings models which have the ability to capture nonlinear patterns in risk exposures.

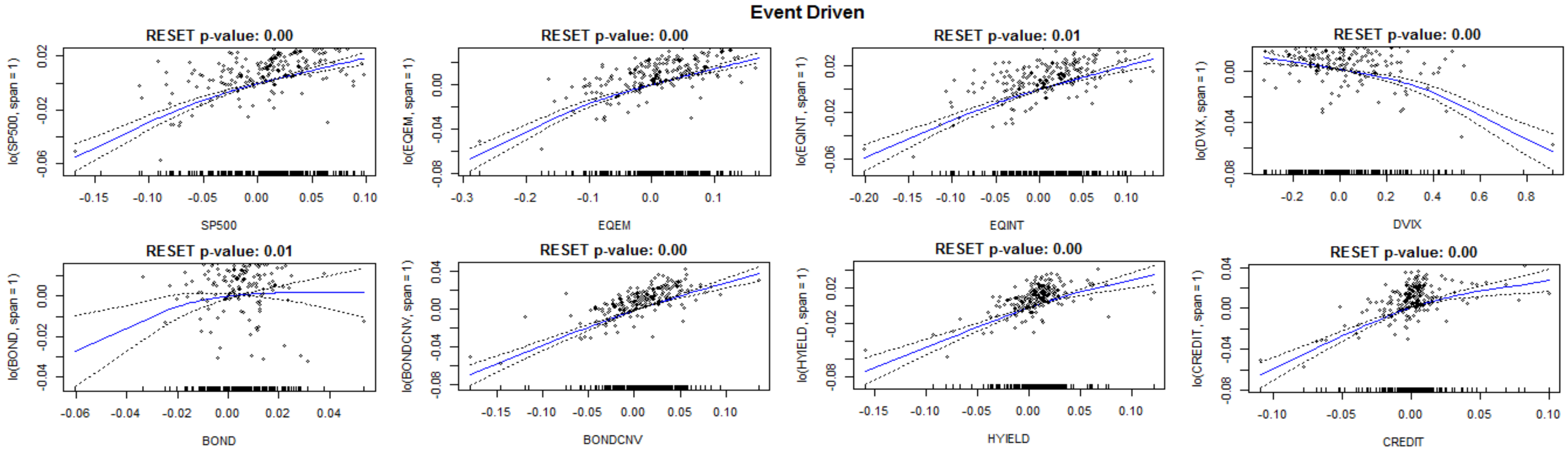
Figure 6.3 Loess Curves - Risk Exposures of Hedge Fund Strategies

The figure shows loess curves (bandwidth = 1) fitted to scatterplots of hedge fund style returns and risk factors as well as pointwise twice-standard-error curves. Holm-Bonferroni-adjusted p-values of the Ramsey RESET test are given on top of the graphs.

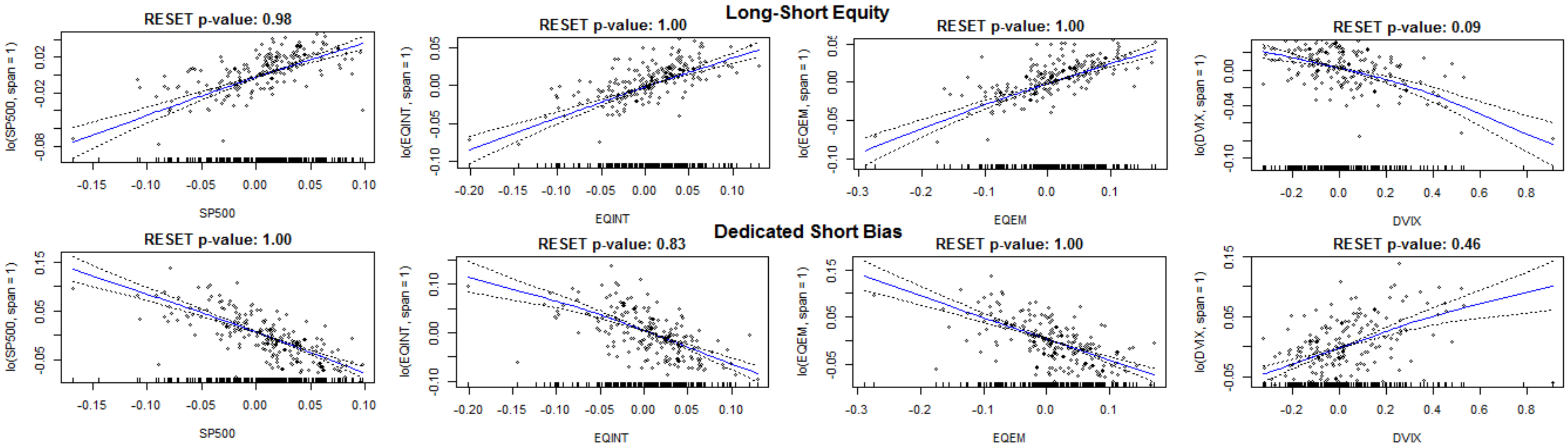
Panel A Arbitrage Styles



Contd.



Panel B Directional Styles



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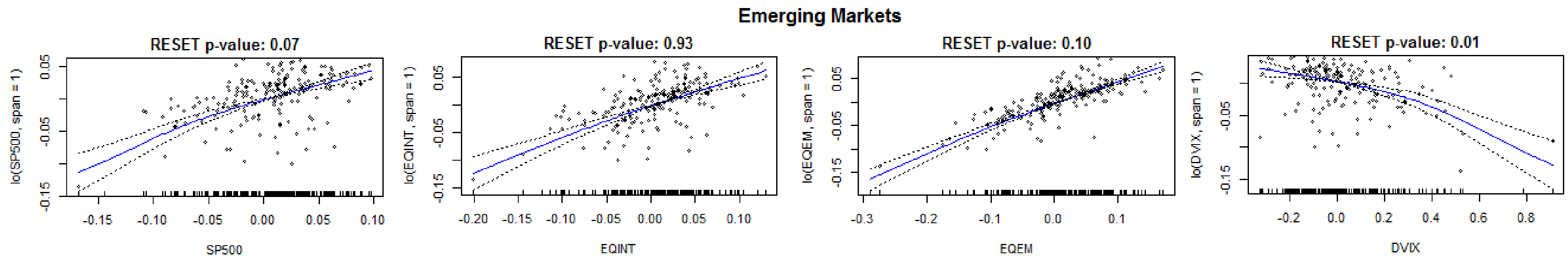
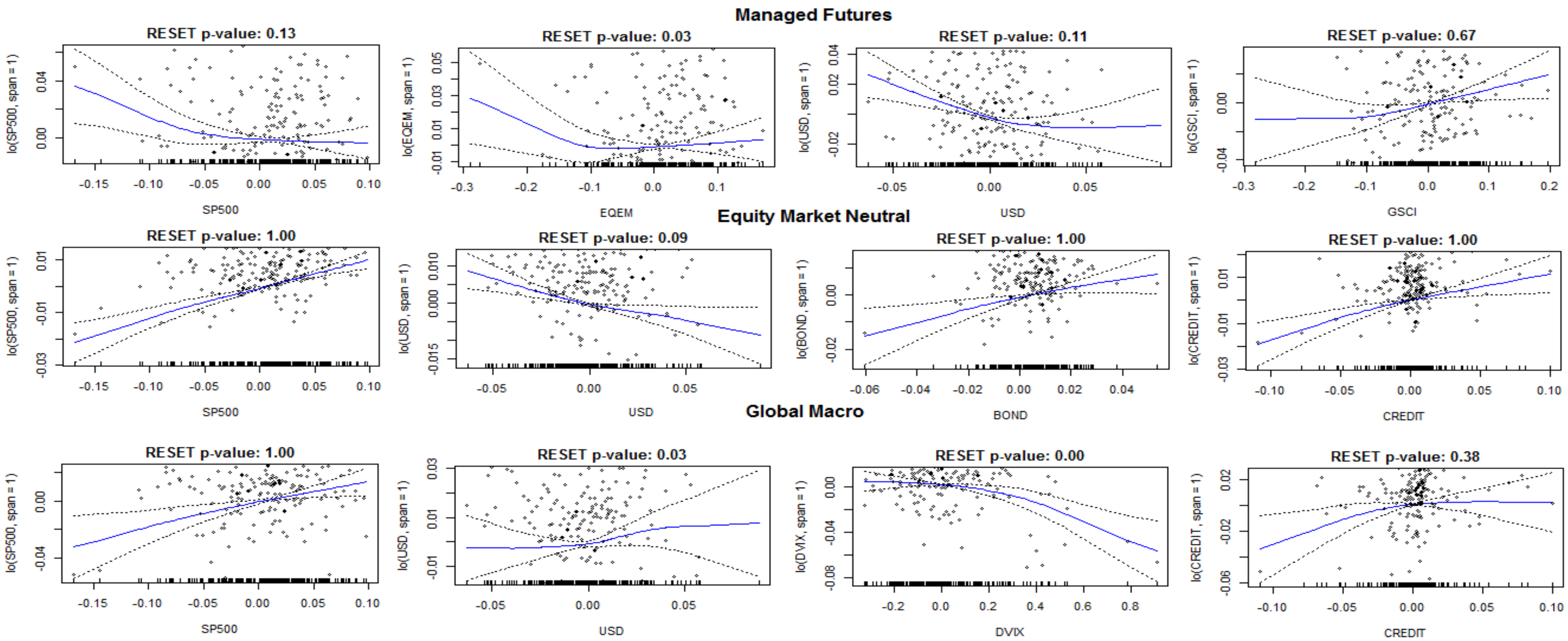


Panel C Managed Futures/CTA, Equity Market Neutral, Global Macro



Contd.

Panel D Multi-Focus

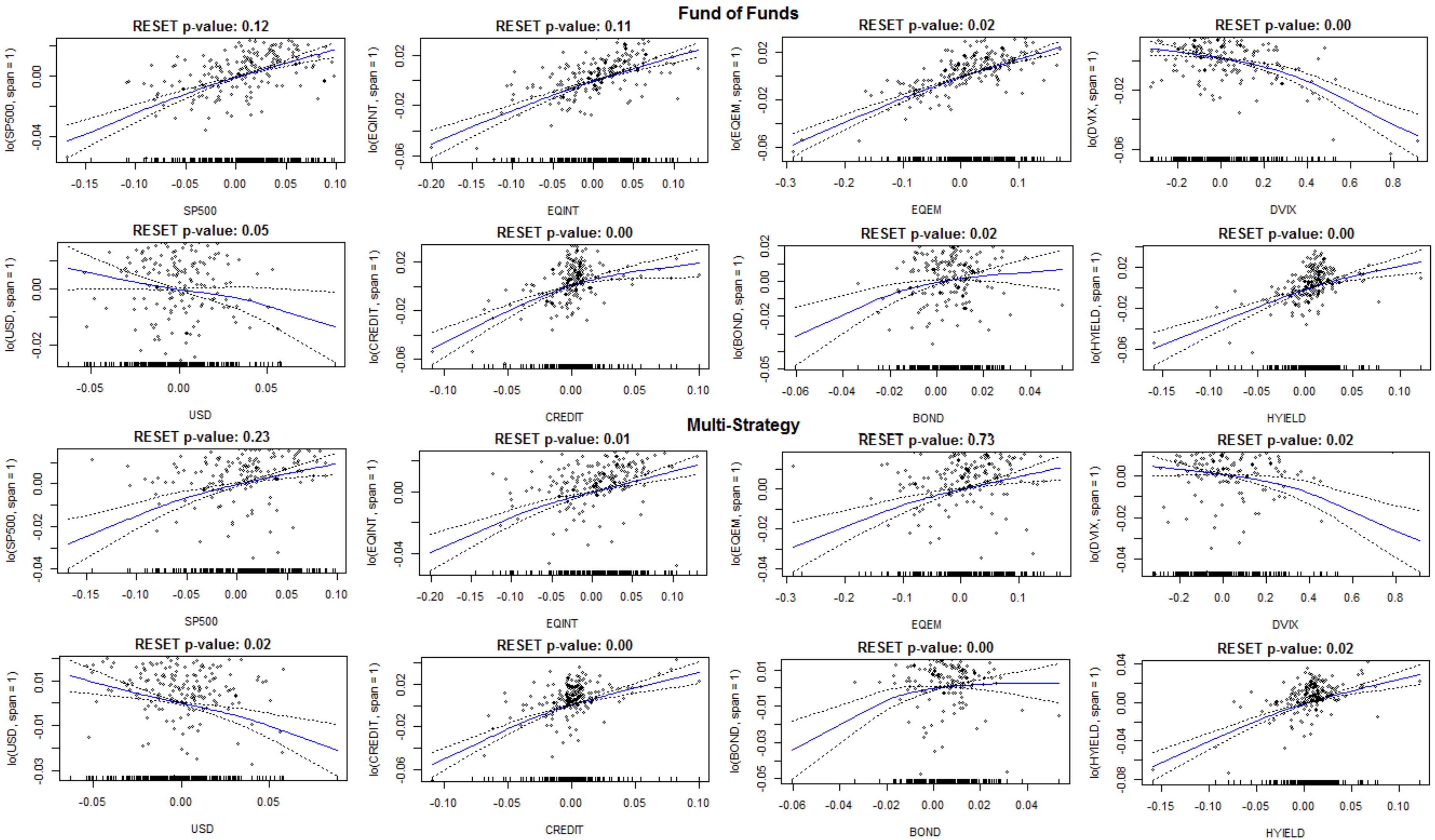
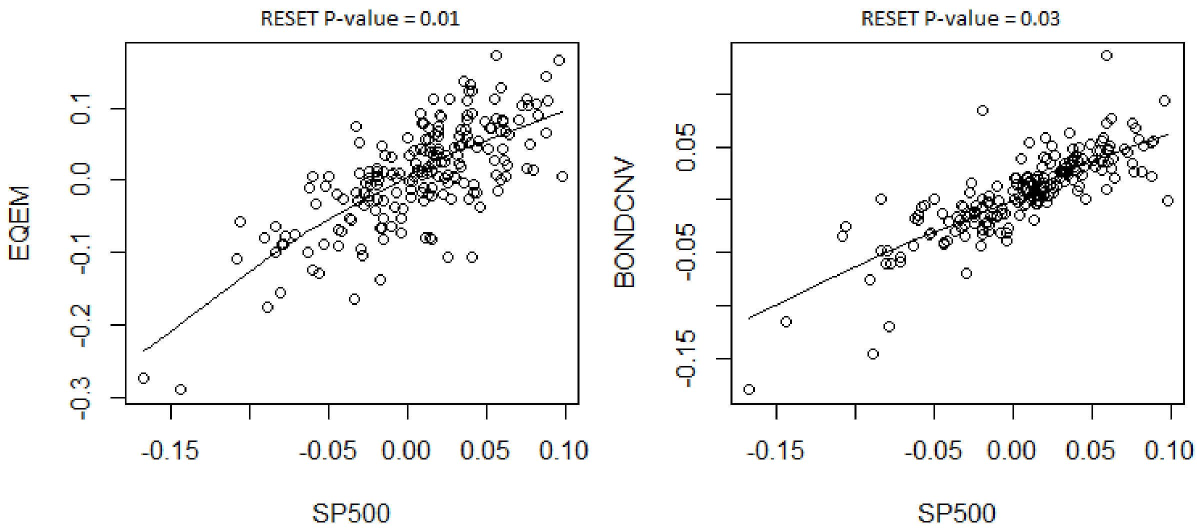


Figure 6.4 Nonlinear Relationships Between Risk Factors



6.3 In-Sample Fit Statistics

The purpose of this section is to analyse the performance of nonparametric models with various fitting procedures and variable selection algorithms (see Section 5.1) and compare them with linear multi-factor models. The list with all the models is given in Table 5.1. The models differ by type of the regression – linear or nonparametric, type of the base smoother in nonparametric models – loess, cubic splines or regression splines, set of risk factors employed in the models – FH7, HL6 or 14-factors, and usage of automatic variable selection procedures.

As explained in Section 5.1.5 the models are fitted via a rolling window procedure and evaluated in-sample and out-of-sample. In-sample results are presented here and out-of-sample results are given in the next section. Table 6.5 reports in-sample goodness of fit statistics R^2 (Panel A) and the AIC (Panel B) averaged across all estimation windows. In theory higher values of R^2 and lower values of the AIC are preferred, since they represent better model fit. In Table 6.5 the model with the highest R^2 (the lowest AIC) is highlighted in bold for each hedge fund style.

The following conclusion can be drawn from the table. Firstly, nonparametric models overall perform better than linear models across all the styles. For instance, all GAMs except one (RGAMS6) have higher R^2 and lower AIC than the seven-factor Fung and Hsieh (2004b) model and the six-factor Hasanhodzic and Lo (2007) model. These results suggest that accounting for nonlinear hedge fund risk exposures is important and GAMs are able to capture nonlinearities better than the standard seven-factor Fung and Hsieh (2004b) model. Furthermore, consistent with earlier findings about stronger nonlinear effects in arbitrage styles, the difference between explanatory power of linear and nonparametric models in the Convertible Arbitrage, the Fixed Income Arbitrage and the Event Driven styles is higher than in directional styles including the Long-Short Equity, the Dedicated Short Bias and the Emerging Markets.

Secondly, the 14-factor models with variable selection clearly outperform the six-factor models without variable selection. This applies to all models regardless of the type. For instance, the average R^2 of the 14-factors GAMs using splines and loess and automatic variable selection is 0.71 and 0.62 respectively, comparing with 0.45 and 0.42 for their six-factor counterparts without variable selection. Thus, exposures to alternative beta beyond standard asset classes are clearly important for pricing hedge funds, and customizing the set of factors individually for each category helps to account for style effects.

Thirdly, the goodness of fit statistic varies substantially across the models. GAMS14 model, i.e. a GAM based on cubic splines and variable selection via shrinkage procedure, has the highest average R^2 of 0.71 among all the models; SGAML14 model, i.e. a GAM based on loess smoothers with bandwidth of 1 and the AIC variable selection, has an average R^2 of 0.62 and is the third best model after GAMS14 and MARS14. The fact that GAMS14 model outperforms SGAML14 model in-sample is likely to be due to its higher flexibility. The smoothness parameter in GAMS14 model is adjusted automatically for each variable (see Section 5.1.2.2), whereas smoothness of loess is controlled by the bandwidth parameter which is set to its highest possible value of 1 for all the variables and that leads to smoothest possible fit (see Section 5.1.2.1.1). The difference can also be due variable selection method employed in the models, i.e. the shrinkage procedure in GAMS14 and the AIC variable selection in SGAML14. Theoretically, simultaneous estimation and variable selection via the penalized likelihood as in GAMS14 model has some advantages, because it should reduce the sensitivity to the estimation error and address potential instability in factor loading estimates due to the presence of collinear factors (Giamouridis & Paterlini, 2010). However, the difference between these two types of GAMs is more likely to be due to different flexibility levels, rather than variable selection method, since the six-factor GAM using splines and without variable selection also outperform its six-factor loess-based counterpart.

Further, comparing the seven-factor Fung and Hsieh (2004b) model and the six-factor Hasanhodzic and Lo (2007) model, the results are mixed. Overall, the two models have the same average R^2 of 0.36. While the FH7 model works better in directional equity related styles (LSE and DSB), the HL6 model better captures the systematic risk premium in two arbitrage styles (CA and FIA). Better performance of the FH7 model in equity styles can be explained by the presence of the size factor (SCMLC, see Table 4.5) in the model, which captures the size premium, an important factor for equity styles. The HL6 model also slightly outperforms the FH7 model in the Managed Futures category. This is an interesting finding because the trend-following factors in the FH7 model are specifically designed to capture the trading style of the systematic CTA funds, a major group of funds which form the Managed Futures category. That is why it would be expected that the FH7 model would produce better fit than the HL6 model and, perhaps, all other models in this particular styles.

The results however demonstrate the opposite. The HL6 model as well as the six- and the 14-factor GAMs based on splines and loess smoothers have higher R^2 and lower AIC than the FH7 model in the Managed Futures category. These observations suggest that hedge fund studies should not rely exclusively on the FH7 model to accommodate hedge fund nonlinearities because there is not enough empirical evidence to prefer this model to more simple linear models such as the HL6 model or other nonlinear models such as GAMs.

All robust models, both linear and nonparametric, demonstrate lower quality of fit in-sample than their standard ('non-robust') counterparts. For instance, R^2 of the 14-factor linear model and the GAM using loess is 0.56 and 0.62, whereas the robust linear model and the robust GAM have R^2 of 0.44 and 0.47 respectively. This is not surprising, because robust models explicitly trade higher bias in-sample for potentially lower variance out-of-sample. For these models the only true test is an out-of-sample test.

Piecewise linear models based on MARS perform well relatively to both linear models and GAMs. The six-factor MARS model MARS6 outperforms all other six-factor models and the FH7 model. The 14-factor MARS model MARS14 has almost the same R^2 as the best GAM, 0.7 and 0.71 respectively[99].

Panel B contains the results on model performance using the AIC statistic. In contrast to R^2 the AIC makes an adjustment for model complexity[100]. Overall, the main results remain consistent. The 14-factor GAM using splines model strongly outperforms other models as it has the lowest value of the AIC across all styles. The GAM using loess is the second best model; it has lower AIC than the stepwise linear model SLM14. Comparing the FH7 and the

[99] The AIC statistic is not available for MARS; hence, the result based only on R^2 should be interpreted with caution

[100] Adjusted R^2 is not defined for nonparametric models

HL6 models it is noted that the FH7 model fits better directional strategies whereas the HL6 model performs better in arbitrage related styles and the Managed Futures style, though overall their performance is close.

Table 6.5 In-Sample Fit Statistics

The tables show the average values of R^2 (Panel A) and the Akaike Information Criterion (AIC) (Panel B) of five linear models and eight nonparametric models of hedge fund style returns fitted using a rolling window procedure during the period from January 1994 to September 2010. The bottom line reports the average value of the statistic. The higher (lower) is the value of R^2 (AIC) the better is model fit. The highest (lowest) value of R^2 (AIC) for each style is shown in bold type.

Panel A: Average R^2

	Linear Models					Nonparametric Models							
STYLE	**FH7**	**HL6**	**SLM14**	**RLM6**	**RLM14**	**GAMS6**	**GAMS14**	**MARS6**	**MARS14**	**GAML6**	**SGAML14**	**RGAMS6**	**RGAMS14**
CA	0.21	0.28	0.40	0.18	0.18	0.38	**0.69**	0.37	0.66	0.37	0.54	0.16	0.23
DSB	0.73	0.60	0.75	0.58	0.71	0.63	**0.84**	0.64	0.83	0.64	0.79	0.58	0.73
EM	0.46	0.43	0.78	0.38	0.73	0.49	**0.82**	0.52	0.81	0.48	0.80	0.39	0.70
EMN	0.26	0.24	0.28	0.16	0.13	0.27	0.41	0.30	**0.45**	0.29	0.34	0.13	0.14
ED	0.52	0.49	0.65	0.43	0.54	0.64	**0.81**	0.65	0.80	0.61	0.76	0.50	0.54
FIA	0.13	0.27	0.38	0.10	0.10	0.45	**0.71**	0.45	0.60	0.37	0.47	0.12	0.08
GM	0.11	0.20	0.37	0.09	0.14	0.25	**0.53**	0.30	0.50	0.24	0.41	0.16	0.18
LSE	0.59	0.42	0.88	0.38	0.85	0.50	**0.92**	0.57	**0.92**	0.45	0.89	0.45	0.84
MF	0.22	0.24	0.27	0.18	0.15	0.41	**0.50**	0.47	0.48	0.31	0.38	0.37	0.41
MS	0.16	0.31	0.39	0.24	0.28	0.38	0.58	0.39	**0.61**	0.36	0.45	0.28	0.35
FoF	0.50	0.42	0.81	0.39	0.76	0.50	**0.86**	0.54	**0.86**	0.47	0.83	0.46	0.78
HFC	0.45	0.39	0.75	0.31	0.66	0.47	**0.83**	0.52	0.82	0.44	0.77	0.40	0.67
Average	0.36	0.36	0.56	0.29	0.44	0.45	**0.71**	0.47	0.70	0.42	0.62	0.33	0.47

Panel B: Average AIC[101]

	Linear Models			Nonparametric Models			
STYLE	FH7	HL6	SLM14	GAMS6	GAMS14	GAML6	SGAML14
CA	-662	-681	-703	-705	**-771**	-693	-725
DSB	-518	-474	-530	-487	**-576**	-478	-542
EM	-486	-482	-593	-497	**-615**	-487	-602
EMN	-839	-838	-846	-846	**-860**	-839	-850
ED	-714	-710	-755	-755	**-823**	-736	-791
FIA	-700	-726	-745	-763	**-819**	-742	-760
GM	-536	-551	-579	-562	**-603**	-552	-583
LSE	-597	-558	-739	-576	**-781**	-558	-750
MF	-477	-482	-486	-511	**-522**	-487	-496
MS	-723	-753	-771	-775	**-810**	-760	-779
FoF	-716	-699	-827	-718	**-861**	-705	-836
HFC	-646	-638	-744	-657	**-784**	-642	-751
Average	-634	-633	-693	-654	**-735**	-640	-705

Next, Table 6.4 reports most important variables for each style as selected by variable selection procedures embedded in all 14-factor models. Variables selected in models in more than 50% of rolling windows are marked as '**' for linear terms, and '++' for nonlinear terms. A few caveats are required before the discussion of results. Among the four nonparametric models (SGAML14, GAMS14, RGAMS14, MARS14) only the GAM using loess (SGAML14) explicitly defines a functional form of predictors either as linear or nonlinear as part of its output[102]. The GAM using spline (GAMS14) does not report the functional form of the terms, and instead outputs the number of effective degrees freedom, which can be used to infer the functional form. However, the outcome of classification into linear and nonlinear terms depends on the choice of the EDF thresholds. Based on extensive

[101] The AIC statistics for component-wise gradient boosted models RLM6, RLM14, RGAM6, and RGAM14 as well as multivariate adaptive spline model MARS14 are not reported because the AIC can be calculated only approximately for these models and comparison with other models may not be accurate. However, other goodness of fit measures exist, such as *percentage deviance explained* which can be used for comparison. The results on relative model fit using deviance, not reported here, are consistent with those reported in Panel A based on R^2.

[102] This is achieved through the AIC variable selection algorithm. The algorithm adds sequentially all the variables into the model as linear and loess terms. It evaluates model fit and decides whether to leave the variable and in what form, linear or loess, or to omit the variable at all. Thus, all the variables which enter the model as loess terms are considered as nonlinear.

simulation and empirical analysis it has been decided that variables significant at 10% level and having the EDF below 1.5 are recognized as linear (because visually they resemble straight lines) and above 1.5 as nonlinear[103]. Also, there is an issue with the automatic classification of risk exposures in the robust GAM and the MARS model (RGAMS14 and MARS14); these models do not provide a single smoothing parameter such as EDF to evaluate the patterns of risk exposures. Hence, the assessment of nonlinearities (beyond visual analysis) is complicated for these models. Therefore all the variables selected in these models are reported in Table 6.4 as nonlinear, i.e. marked as '++' and the results can be used only for the analysis of factors selected and not for the evaluation of the form of risk exposures. In addition, the results in Table 6.4 can be affected by the concurvity between the factors, as discussed in Section 6.2. However, it is expected that variable selection procedures will mitigate the issue, because they are designed to identify variables which maximize the explanatory power of the models.

Given these limitations interpretation of results in Table 6.4 should be exercised with caution. The main focus in Table 6.4 is on the SGAML14 model. Several comments can be made regarding the risk exposures of hedge fund styles. In arbitrage styles (CA, ED, FIA) almost all the factors appear to be important, except for commodity and currency variables in the Convertible Arbitrage, bond in the Event Driven and SMB in the Fixed Income Arbitrage styles. Many of the exposures are nonlinear, though there are some discrepancies

[103] In the GAMS14 model based on cubic splines the fitting procedure estimates the optimal degrees of smoothness for each variable; then it calculates the estimated degrees of freedom (EDF) as well as approximate standard errors for all the variables. The EDF is a characteristic of the complexity of the term; for instance, if EDF=1, then the term is linear. The functional form of the term can be defined using either the EDF or the significance test or a combination of both. Based on extensive empirical and simulation analysis, which involved visual examination of risk exposure patterns for different values of the EDF, it has been decided to apply following definitions of functional forms in the GAM using splines: Linear=[P-value<0.1;0.5<EDF⩽1.5], Nonlinear=[P-value<0.1;EDF>1.5], otherwise the variable is considered to be not significant and not reported in Table 6.4. P-value is the approximate p-value of the significance test. The EDF thresholds of 0.5 and 1.5 have been selected so, because visually GAMs with the EDF between 0.5 and 1.5 look very close to straight lines. It is important to understand that this choice does not in any way affect the model fit. It affects only the results in Table 6.4, i.e. which variables are considered as linear and nonlinear.

between the SGAML14 and the GAMS14 models. Overall, the findings on significant nonlinearities are consistent with the notion that arbitrage styles are nonlinearly related to market factors due to the presence of financial distress risk in their strategies (Agarwal & Naik, 2004). Also, in line with Agarwal and Naik (2004) these styles exhibit significant exposure to Fama and French (1993) factors, perhaps, because small and high book-to-market firms are more likely to be in distress.

Among directional styles the risk exposure of the Long-Short Equity style to US equity is linear, as suggested by the SGAML14 and the GAMS14 models; in the Dedicated Short Bias style exposure to US equities is linear according to the SGAML14 model, and nonlinear according to the GAMS14 model. Both styles exhibit nonlinear exposure to international equities. However, it could be due to asymmetric relationship between US equity returns and international equity returns. Emerging markets funds demonstrate nonlinear relation to emerging markets equity.

In the Equity Market Neutral style similar to findings in the previous section (Section 6.2) there is a weaker evidence of systematic risk exposures than in other styles. This style exhibits some exposure to equity variables, and currency, while Fama and French (1993) and Carhart's (1997) factors do not appear important in most of the periods.

The Managed Futures style exhibits risk exposure to most of the variables including equities, bonds, currency and commodity factors. However, there is substantial model uncertainty, as results vary across the models. Similar to the Equity Market Neutral style this style demonstrates the lowest linear and higher order correlations with traditional and alternative factors among all the styles, as Figure 6.2 earlier reveals. Therefore, it is not surprising that uncertainty about systematic risk is high. Other studies have faced similar problem of low explanatory power of factor-models in this style (Hasanhodzic & Lo, 2007).

The remaining hedge fund styles demonstrate presence of nonlinear effects to different risk factors. Overall, the findings are consistent with the evidence in other studies that hedge funds have nonlinear/asymmetric risk exposures to different risk factors, and that these asymmetries appear to different risk factors than the market (Agarwal & Naik, 2004; Giannikis & Vrontos, 2011). Ignoring the presence of these nonlinearities is likely to result in misleading conclusions about hedge funds.

Table 6.6 Most Important Factors

This table shows important linear and nonlinear exposures of hedge fund styles as selected by automatic variable selection procedures in the models. The models are fitted via a rolling window procedure. In the SGAML14 and the GAMS14 models a factor is classified as important linear factor and marked as '**' when it is selected in a linear form in at least 50% of the windows, and as a nonlinear factor and marked as '**' when it enters the model in a nonlinear term in at least 50% of the windows. In the linear models SLM14 and RLM14 the variables appearing in more than 50% of the windows are always marked as linear '++'; and the variables selected in the RGAMS14 and the MARS14 models in more than half of the windows are always marked as nonlinear '++'.

Style	Model	SP500	USD	BOND	CREDIT	GSCI	DVIX	SMB	HML	UMD	EQINT	EQEM	HYIELD	BONDINT	BONDCNV
CA	SLM14	**		**	**				**					**	**
	RLM14				**			**					**		
	SGAML14	++			**		++	++	++	**		++		**	++
	GAMS14	++			++			++		++	++	++	++		++
	RGAMS14							++	++	++			++		++
	MARS14	++			++			++		++	++	++	++		++
DSB	SLM14	**	**	**				**						**	**
	RLM14	**					**	**	**	**					**
	SGAML14	**		**			++	**			++				++
	GAMS14	++					++	++	++		++		++		**
	RGAMS14	++					++	++	++		++				++
	MARS14	++						++	++		++		++		++
EM	SLM14	**	**	**					**	**		**			**
	RLM14		**	**		**				**		**			**
	SGAML14		**	**			++			**		++			
	GAMS14									**		++			
	RGAMS14		++	++		++		++		++		++			++
	MARS14			++						++		++		++	++
EMN	SLM14	**	**		**							**			
	RLM14	**		**							**				**
	SGAML14	**	++		**				++			**			**
	GAMS14											++			++
	RGAMS14		++								++				
	MARS14	++	++		++		++					++			++
ED	SLM14							**	**	**		**	**	**	**
	RLM14		**		**	**		**	**	**	**	**	**		**
	SGAML14		**		++		++	**	**			++	**		**
	GAMS14				++				**		++	++	++		**
	RGAMS14				++			++	++		++	++	++		++
	MARS14	++			++		++		++		++	++			++

Contd.

Style	Model	SP500	USD	BOND	CREDIT	GSCI	DVIX	SMB	HML	UMD	EQINT	EQEM	HYIELD	BONDINT	BONDCNV
FIA	SLM14	**	**	**	**		**		**					**	**
	RLM14		**	**	**	**							**		**
	SGAML14		**	**	++		++		**					**	**
	GAMS14	++		++	++		**			++	++	++	++	++	++
	RGAMS14		++		++	++							++		++
	MARS14				++		++		++			++		++	++
GM	SLM14			**					**	**		**		**	**
	RLM14			**						**		**			**
	SGAML14			**			++		**						**
	GAMS14						++		++					++	++
	RGAMS14	++	++	++						++		++	++		++
	MARS14	++	++	++			++		++						++
LSE	SLM14	**		**			**	**		**		**	**		**
	RLM14	**	**	**	**	**	**	**	**	**	**	**	**		**
	SGAML14	**		**			++	++		**		++			++
	GAMS14	**			++		++	++		++		++			++
	RGAMS14		++	++	++	++	++	++	++	++	++	++	++		++
	MARS14	++			++		++	++		++		++			++
MF	SLM14	**	**	**	**	**			**			**		**	
	RLM14			**	**	**				**				**	
	SGAML14		++	**	**	**		++	**			++	++		
	GAMS14	++				++							++		
	RGAMS14	++	++	++	++	++		++		++		++	++	++	++
	MARS14	++	++	++	++	++							++		++
MS	SLM14				**		**						**		**
	RLM14		**		**			**			**		**		**
	SGAML14				**		++	++	**						**
	GAMS14						++	++	++		++				
	RGAMS14		++	++			++	++	++		++		++		++
	MARS14		++		++		++	++	++		++	++	++		++
FoF	SLM14		**	**		**	**	**	**	**		**			**
	RLM14		**	**	**	**	**	**	**	**	**	**	**	**	**
	SGAML14						++		**	**		**	**		**
	GAMS14				++				++	**	++	++			++
	RGAMS14		++	++	++	++	++	++	++	++	++	++	++		++
	MARS14				++		++	++	++	++	++	++			++
HFC	SLM14		**	**			**		**	**		**		**	**
	RLM14		**	**						**	**	**	**		**
	SGAML14			++			++		**	**				**	**
	GAMS14			++	++		++		++	**	++			++	++
	RGAMS14	++	++	++	++	++	++	++		++	++	++	++		++
	MARS14	++	++	++	++		++	++	++	++	++	++			++

6.4 Out-of-Sample Fit Statistics

The previous section established common nonlinear patterns in risk exposures of various hedge fund styles. The results have been validated in an in-sample test by applying nonparametric models to modeling hedge fund style returns. However, greater flexibility of nonparametric models poses concerns of potential data overfitting or data snooping bias, since these models are more prone to estimation risk than linear multi-factor models. The problem has long been recognized in traditional asset pricing literature[104] and more recently in hedge fund studies[105]. It has been proposed that an out-of-sample test should provide some measure of protection against data mining, as models are tested using the data not used in the estimation of the model itself[106]. Accordingly, this section presents the results of an out-of-sample analysis of linear and nonparametric models.

Table 6.7 reports out-of-sample annualized root-mean squared error (RMSE) (Panel A) and mean absolute error (MAE) (Panel B) of all the models during the period from January 2004 through September 2010. For each style the model with the lowest value of the RMSE and the MAE is highlighted in bold. Several comments are in order.

Firstly, a brief comparison of in-sample and out-of-sample results in Table 6.5 and Table 6.7 reveals that models that provide better quality of fit in-sample do not necessarily perform well out-of-sample. The GAM using cubic splines (GAMS14) which has the highest in-sample R^2 performs a little worse out-of-sample than the GAM using loess (SGAML14) which is only

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[104] See, for example, Lo and MacKinlay (1990), Foster, Smith, and Whaley (1997) and Rapach and Wohar (2006)

[105] See, among others, Agarwal and Naik (2004), Amenc et al. (2010))

[106] Ashley et al. (1980, p. 1149) discuss the arguments in favour of using an out-of-sample test to establish Granger causality between two time-series and state that "… a sound and natural approach to such tests [Granger causality tests] must rely primarily on out-of-sample forecasting performance of models relating the original (non-prewhitened) series of interest".

the third best model in-sample. The average RMSE and MAE of the GAMS14 model is 6.7% and 1.34% respectively, while the average RMSE and MAE of the SGAML14 model is 5.7% and 1.19%. As explained earlier the GAMS14 model is more flexible in adjusting to the data than SGAML14 model, because its smoothing parameters are tuned automatically for each term. However, the reduction of model bias leads to an increase in the variance of the model error and a slightly worse fit out-of-sample when a new dataset is used. This result is quite unexpected, because in theory the GAMS14 model has some appealing statistical properties related to variable selection via a shrinkage procedure and optimal smoothness selection based on the generalized cross validation method (see Section 5.1.2.2). The difference in tracking error between the two models cannot be attributed to variables selection procedures, because the version of these two models without variable selection (i.e. the GAML6 and the GAMS6 models) produce the same relative result: the RMSE of the GAMS6 is 6.7% against 6.2% for the GAML6. It follows from the out-of-sample results that the GAM using loess should be preferred to other nonparametric models, since it delivers the best performance out-of-sample. This is an important finding, because it shows that the choice of the model that accommodates nonlinearities matters. It also shows that the constraint on the flexibility of the SGAML14 model imposed by the bandwidth parameter set to 1 helps to prevent data overfitting.

Secondly, as observed from the table the best nonparametric model SGAML14 has lower tracking error and MAE than the best linear model the SLM14: the average RMSE and MAE of the SGAML14 model is 5.7% and 1.19%, while the figures for SLM14 model are 5.8%, and 1.23% respectively. Although the difference between the two models is quite small, it still provides evidence that nonlinear patterns captured with the nonparametric model are genuine, rather than an artefact of a noisy data. If nonlinear patterns were spurious, a more complicated nonparametric model would have a higher out-of-sample error. For instance, Amenc et al. (2010) examine a range of models which are designed to account for nonlinearities and conclude that going beyond the linear case does not necessarily improve out-of-sample performance. The results presented in Table 6.7 prove that the methodology matters, i.e. nonlinearities can be captured if the model is selected appropriately. The difference between the linear and the nonparametric models is small, because the out-of-sample period covers only five years of observations. There are not enough out-of-sample observations at the boundaries of the return distribution where nonlinear patterns are particularly pronounced. Furthermore, although the difference in performance is small it can still be economically significant for investors. This question is examined in more detail in the next two chapters.

Regarding the variation of the tracking error across the styles, the SGAML14 model performs particularly well relative to other models in the Managed Futures and the Convertible Arbitrage styles. This is because these styles have multiple nonlinearities related to various market factors as highlighted before.

The third comment is related to the linear models from the hedge fund literature, i.e. the FH7 and the HL6. The FH7 model demonstrates the highest average tracking error and MAE among all the models, including the six-factor models. FH7 model's average RMSE and MAE is 7% and 1.43%, while HL6 model's average RMSE and MAE is 6.3% and 1.36%. The FH7 model outperforms the HL6 model only in two styles (DSB and MF) in terms of the RMSE and in three styles in terms of the MAE (DSB, GM, and MF). In the Managed Futures style some of nonparametric models also outperform the FH7. Poor performance of this model out-of-sample highlights limited applicability of trend following factors to hedge fund styles outside the CTA domain and even within the Managed Futures styles when compared with nonparametric models.

The robust linear model demonstrates a very good performance out-of-sample, despite the mediocre results in-sample. This finding suggests that the noise in the data can affect the results and by using robust statistics the problem can be mitigated. Nevertheless, the best nonparametric model still has slightly lower tracking error than the robust linear model, thus confirming the genuine nature of nonlinear patterns.

Table 6.7 Out-of-Sample Performance

The tables show the out-of-sample root-mean-square error (RMSE) in Panel A and the mean absolute error (MAE) in Panel B of five linear models and ten nonparametric models fitted to the returns of hedge fund style indices via a rolling window procedure with 120-month estimation window and 1-month ahead prediction. The bottom line in the tables contains the average RMSE (MAE) across all the styles for each model. Models with the lowest RMSE (MAE) for each style are shown in bold type.

Panel A: Root-Mean-Squared Error

	Linear Models					Nonparametric Models							
Style	**FH7**	**HL6**	**SLM14**	**RLM6**	**RLM14**	**MARS6**	**MARS14**	**GAML6**	**SGAML14**	**GAMS6**	**GAMS14**	**RGAMS6**	**RGAMS14**
CA	0.089	0.068	0.062	0.077	0.078	0.084	0.067	0.070	**0.058**	0.071	**0.058**	0.092	0.092
DSB	0.096	0.119	0.111	0.108	0.113	0.117	0.122	0.119	0.111	0.115	0.125	0.109	**0.089**
EM	0.089	0.075	0.058	0.066	**0.045**	0.085	0.069	0.072	0.057	0.090	0.067	0.089	0.076
EMN	0.040	**0.036**	0.039	0.037	0.039	0.042	0.046	0.038	0.040	0.038	0.049	0.041	0.040
ED	0.046	0.042	0.038	0.041	0.040	0.042	0.040	0.039	**0.037**	0.040	0.048	0.048	0.049
FIA	0.076	0.064	0.054	0.067	0.070	0.067	0.074	0.062	**0.053**	0.071	0.064	0.079	0.079
GM	0.065	0.061	0.061	0.062	**0.058**	0.068	0.093	0.059	0.060	0.062	0.096	0.060	0.060
LSE	0.064	0.045	0.035	0.045	0.034	0.063	0.046	0.048	**0.033**	0.059	0.037	0.056	0.056
MF	0.116	0.118	0.127	0.121	0.120	0.111	0.134	0.114	0.118	0.104	0.135	**0.101**	0.103
MS	0.058	0.045	0.045	0.047	0.049	**0.040**	0.046	0.043	0.044	0.042	0.045	0.058	0.058
FoF	0.047	0.041	0.033	0.041	**0.032**	0.048	0.033	0.040	0.034	0.046	0.036	0.046	0.043
HFC	0.052	0.041	0.037	0.044	**0.033**	0.049	0.046	0.040	0.036	0.043	0.043	0.051	0.049
Average	0.070	0.063	0.058	0.063	0.059	0.068	0.068	0.062	**0.057**	0.065	0.067	0.069	0.066

Panel B: Mean Absolute Error

	Linear Models					Nonparametric Models							
Style	**FH7**	**HL6**	**SLM14**	**RLM6**	**RLM14**	**MARS6**	**MARS14**	**GAML6**	**SGAML14**	**GAMS6**	**GAMS14**	**RGAMS6**	**RGAMS14**
CA	0.0155	0.0126	0.0114	0.0132	0.0134	0.0142	0.0118	0.0125	**0.0111**	0.0130	0.0113	0.0146	0.0150
DSB	0.0208	0.0238	0.0215	0.0231	0.0207	0.0247	0.0232	0.0236	0.0212	0.0241	0.0260	0.0238	0.0193
EM	0.0202	0.0172	0.0131	0.0149	**0.0097**	0.0185	0.0130	0.0167	0.0124	0.0178	0.0134	0.0176	0.0118
EMN	0.0075	**0.0070**	0.0073	**0.0070**	0.0071	0.0080	0.0083	0.0072	0.0073	0.0073	0.0093	0.0075	0.0072
ED	0.0098	0.0091	**0.0080**	0.0090	0.0084	0.0090	0.0086	0.0087	**0.0080**	0.0089	0.0094	0.0095	0.0093
FIA	0.0119	0.0117	0.0102	0.0105	0.0111	0.0111	0.0125	0.0109	**0.0101**	0.0114	0.0116	0.0115	0.0116
GM	0.0126	0.0133	0.0130	0.0126	0.0121	0.0140	0.0172	0.0128	0.0129	0.0134	0.0172	**0.0120**	0.0122
LSE	0.0139	0.0103	0.0082	0.0106	0.0081	0.0137	0.0099	0.0104	**0.0078**	0.0127	0.0082	0.0112	0.0092
MF	0.0272	0.0287	0.0303	0.0289	0.0287	0.0262	0.0299	0.0280	0.0277	0.0247	0.0289	**0.0242**	0.0246
MS	0.0116	0.0099	0.0097	0.0099	0.0097	**0.0088**	0.0094	0.0092	0.0093	0.0091	0.0093	0.0108	0.0105
FoF	0.0101	0.0093	0.0073	0.0093	0.0072	0.0104	**0.0071**	0.0091	0.0074	0.0096	0.0073	0.0093	0.0078
HFC	0.0108	0.0097	0.0079	0.0098	**0.0074**	0.0106	0.0103	0.0091	0.0080	0.0095	0.0092	0.0100	0.0088
Average	0.0143	0.0136	0.0123	0.0132	0.0120	0.0141	0.0134	0.0132	**0.0119**	0.0135	0.0134	0.0135	0.0123

The next Table 6.8 summarizes the results on relative model ranking based on the out-of-sample performance from Table 6.7. It can be seen from the table that the GAM using loess dominates both the 14-factor models with variable selection and the six-factor models without variable selection according to the RMSE and the MAE criteria. The stepwise linear model (SLM14) and the robust linear model (RLM14) are on the second place in model ranking. The fact that the robust linear model performs better than all the nonparametric models except the loess GAM suggests that the concern about overfitting the noisy data is partly justified; however, selecting the right model helps mitigating the problem.

Following the out-of-sample results, the two models selected for further analysis in the next two chapters are the SGAML14, i.e. the stepwise GAM using loess smoothing, and the SLM14, i.e. the stepwise linear regression model.

Table 6.8 Out-of-Sample Model Ranking

The tables report ranking of 15 linear and nonparametric models based on their out-of-sample root-mean-square error (RMSE) and mean absolute error (MAE). Panel A contains ranking of all the models and in Panel B the results for the six-factor and the 14-factor models are presented separately.

Panel A

	Model	
Rank	RMSE	MAE
1	SGAML14	SGAML14
2	SLM14	RLM14
3	RLM14	RGAMS14
4	GAML6	SLM14
5	RLM6	GAML6
6	HL6	RLM6
7	GAMS6	GAMS14
8	RGAMS14	MARS14
9	GAMS14	GAMS6
10	MARS6	RGAMS6
11	MARS14	HL6
12	RGAMS6	MARS6
13	FH7	FH7

Panel B

	6-Factor Models		14-Factor Models	
Rank	RMSE	MAE	RMSE	MAE
1	GAML6	GAML6	SGAML14	SGAML14
2	RLM6	RLM6	SLM14	RLM14
3	HL6	GAMS6	RLM14	RGAMS14
4	GAMS6	RGAMS6	RGAMS14	SLM14
5	MARS6	HL6	GAMS14	GAMS14
6	RGAMS6	MARS6	MARS14	MARS14
7	FH7[a]	FH7		

[a] The Fung and Hsieh model contains seven factors

6.5 Conclusion

This chapter examines the fundamental issue in hedge fund research concerning hedge funds' nonlinear exposures to systematic risk. Earlier studies have identified some nonlinear patterns; however, these nonlinearities have not been confirmed out-of-sample. The results of the analysis presented in this chapter contribute to the literature as they yield several important findings.

First of all, it has been identified that nonlinearities affect most of the hedge fund styles, though to a varying degree. Styles which focus on exploiting arbitrage opportunities and relative security mispricing (the Convertible Arbitrage, the Fixed Income Arbitrage and the Event Driven) exhibit similar nonlinear exposures to different types of risk including the equity market risk, the credit risk and the interest rate risk. Consistent with the evidence in Fung and Hsieh (2002b), Agarwal and Naik (2004), Duarte et al. (2007) and Agarwal, Fung, et al. (2011) the exposures of these styles typically resemble a payoff of a short put option position. Such nonlinear exposures can be explained by high sensitivity of arbitrage strategies to adverse market events. When the market volatility is low and the yield spreads do not vary dramatically arbitrage styles tend to generate small profits, which are largely unaffected by the magnitude of market gains; however, during financial distress situations, the yield spreads sharply rise, the market volatility increases and arbitrage strategies generate disproportionally large losses. Multi-focus styles, including the Multi-Strategy and the Fund of Funds categories also exhibit many nonlinear patterns in different risk exposures. Directional styles, including the Long-Short Equity, the Dedicated Short Bias, and the Emerging Markets in contrast to non-directional styles have predominantly linear risk exposures in their focus markets. In line with the studies of Fung and Hsieh (2004a) and

Fung and Hsieh (2011) it is found that the Long-Short Equity category exhibits significant exposure to Fama and French's (1993) size and value factors and Carhart's (1997) momentum factor, i.e. funds in this category make spread bets (i.e. small vs. large stocks, value vs. growth stocks).

Next, a number of nonparametric techniques are proposed to model hedge fund risks and returns. Although nonparametric techniques have been used in asset pricing before, nonparametric models have not previously been applied in the context of hedge funds. The results of in-sample and out-of-sample tests demonstrate that the nonparametric approach based on a GAM using loess smoothers outperforms standard linear multi-factor models including the seven-factor Fung and Hsieh (2004b) model, the six-factor Hasanhodzic and Lo (2007) model and the 14-factor stepwise linear regression model. Therefore, it is concluded that the nonparametric model captures genuine nonlinear risk exposures in hedge fund styles. This is an important result, as in prior studies there is little evidence of the ability of hedge fund pricing models to capture nonlinear patterns out-of-sample.

Furthermore, evaluation of the seven-factor Fung and Hsieh (2004b) model developed to address the issue of option-like features in hedge funds' risk exposures provides little empirical evidence of its ability to explain hedge fund returns better than other more simple linear models. The explanatory power of the seven-factor Fung and Hsieh (2004b) model and the six-factor Hasanhodzic and Lo (2007) model in-sample is very close, while the latter model provides better quality of fit out-of-sample. In the Managed Futures category, the target style of the seven-factor Fung and Hsieh (2004b) model, it also underperforms nonparametric GAMs, indicating that GAMs captures asymmetric effects in CTAs' risk exposures better.

Summarizing the findings, the key takeaway from this chapter is that there is significant statistical evidence of nonlinearities in-sample and out-of-sample; failure to account for nonlinearities lead to higher model error.

Chapter 7 Results – Assessing Nonlinearities in Individual Funds

The previous chapter reports significant nonlinearities in risk exposures of aggregate hedge fund style portfolios. These nonlinearities can be explored by applying nonparametric models, such as a generalized additive model using loess smoothers. This chapter extends the discussion and examines nonlinearities in individual funds.

7.1 Nonlinearities in Individual Funds

To provide a more comprehensive evaluation of nonlinearities in hedge funds, in this chapter the nonparametric models developed earlier are applied to individual hedge funds. This is required because aggregation of hedge funds in an index might generate spurious nonlinear patters or, on the contrary, offset nonlinear patterns existing in individual funds' exposures (Diez de los Rios & Garcia, 2011). An additional motivation for a fund-level analysis is to investigate whether nonlinearities are associated with superior performance. Investors are not interested in nonlinearities per se; however, if nonlinearities signal skill among fund managers this information could be useful for investors.

To examine the presence of nonlinearities in individual funds it is proposed to classify funds into three categories based on the form of their risk exposures: linear funds, nonlinear funds, and funds without significant systematic risk exposures (see, Section 5.2.1). The procedure employed for classification consecutively fits a linear and a nonlinear model to individual funds' returns and performs a statistical test pertaining to the explanatory power of the models. If the explanatory power of the linear model is above the threshold and the nonlinear model fitted to the residuals of the linear model does not improve the quality of fit substantially, i.e. its explanatory power is below another threshold, then it is concluded that the fund has only linear systematic risk exposures; otherwise, if the incremental explanatory power of the nonlinear model is substantial, the fund is considered a nonlinear fund (i.e. with nonlinear risk exposures); and if none of the models have high enough explanatory power then the fund is described as without significant risk exposures.

To perform this procedure it is required to determine the critical values of the goodness-of-fit measures for the linear and the nonlinear models that will be used in statistical tests. The models employed for classification are the 14-factor stepwise linear regression model SLM14 and the stepwise GAM using loess smoothers SGAML14. These models have proven to be more successful in capturing hedge funds' systematic risk than other models (see Section 6.4); it is evidenced by their superior fit in-sample and lower out-of-sample error. In addition to the 14-factor models two six-factor models the HL6 and the GAML6 are also employed. This is done to test the sensitivity of results to the choice of risk factors. Adjusted R^2 is used to measure the explanatory power of the models[107]. The critical values of R^2 represent the average value of the 95th percentile of the empirical distributions of R^2 obtained by fitting a series of linear and nonparametric models to randomly generated returns. Random returns are bootstrapped with resampling form the pooled distribution of hedge fund returns, as well as generated from the standard normal distribution and t-distribution with one and two degrees of freedom. Since randomly generated returns are

[107] Hereafter in this chapter R^2 indicates a regression's adjusted R^2 unless stated otherwise

unrelated to the two sets of risk factors, the R^2 coefficients reflect goodness of fit of the models that can occur purely by chance.

Table 7.1 Panel A and Panel B report the critical values and percentiles of R^2 distributions over the three non-overlapping periods, 1995-1999, 2000-2004, 2005-2009[108]. Panel A contains the results using the 14-factor models and Panel B uses the six-factor models. Comparing the figures in Panel A and Panel B it is observed that the extended variable set overall leads to higher critical values. This is natural, because 14 factors provide more combinations to fit random return patterns than six factors do. The average critical value of the linear R^2 across the distributions is 0.2787 for the 14-factor model and 0.1645 for the six-factor model. The values of R^2 seem quite high, particularly when compared with the results for standard linear multi-factor models in the literature. For instance, Titman and Tiu (2011) report a median R^2 for individual funds' regressions of just 0.24 using widely adopted seven-factor Fung and Hsieh (2004b) model and 0.42 using a stepwise approach with 31 factors. The median R^2 coefficients of the multi-factor models are clearly not too far away from random regressions' R^2. These results indicate that there is a high chance of spurious model fit particularly when the number of explanatory variables is large. It also suggests that the "reality check" procedure (i.e. comparison of regression fit for hedge funds with the fit for random regressions) adopted in this thesis is warranted and necessary to minimize the risk of making spurious conclusions about the goodness of model fit.

Furthermore, as observed from the table critical values of the nonlinear model are lower than those of the linear model. It is expected, because the nonlinear model is fitted to the residuals of the linear model. After the linear model is fitted the main component in risk

[108] These periods are selected because the nonparametric models require at least 60 monthly observations and the data are available only for 1994-2009

exposures, i.e. the linear trend, is captured and the remaining higher order nonlinear effects are likely to be of lower magnitude. Thus, the average critical value for the nonlinear 14- and six-factor models is 0.1684 and 0.1193 respectively (comparing with 0.2787 and 0.1645 for the linear model, as mentioned above).

R^2 percentiles across four distributions and three sub-periods show small variation. Thus, estimated critical values are robust to deviation from normality in hedge funds' return distributions and can be applied to hedge funds with confidence. Also, critical values are in line with those reported in Bollen (2013). Bollen (2013) reports the critical values of 0.189 for the 14-factor linear model and 0.309 for the 14-factor linear model with one switch in coefficients[109].

Table 7.1 Critical Values of Adjusted R^2

The table reports percentiles of the adjusted R^2 coefficient for the 14-factor (Panel A) and the six-factor (Panel B) linear and nonparametric models fitted over three sub-periods, 1995-1999, 2000-2004 and 2005-2009. The linear models are fitted to random samples drawn from the standard normal distribution, Student's t-distribution with 1 and 2 degrees of freedom, and from the pooled distribution of hedge fund returns bootstrapped with replacement. The nonparametric models are fitted to the residuals of the linear models.

Panel A: 14 factors

	Standard Normal		T-distr. 1 D.F.		T-distr. 2 D.F.		Bootstrap	
Percentile	Adj.R^2 SLM14	Adj.R^2 SGAML14	Adj.R^2 SLM14	Adj.R^2 SGAML14	Adj.R^2 SLM14	Adj.R^2 SGAML14	Adj.R^2 SLM14	Adj.R^2 SGAML14
				1995-1999				
5%	0.09	0.03	0.03	0.03	0.00	-0.03	0.01	-0.02
25%	0.05	0.01	0.05	0.00	0.05	-0.01	0.05	0.01
50%	0.09	0.03	0.10	0.03	0.10	0.02	0.10	0.03
75%	0.15	0.07	0.16	0.07	0.15	0.04	0.16	0.07
95%	0.27	0.18	0.30	0.24	0.23	0.14	0.26	0.17
				2000-2004				
5%	0.10	0.03	0.00	-0.03	0.00	-0.03	0.02	-0.03
25%	0.06	-0.01	0.05	-0.02	0.05	-0.01	0.07	-0.02
50%	0.10	0.03	0.09	0.03	0.10	0.02	0.10	0.02
75%	0.16	0.06	0.16	0.09	0.16	0.06	0.16	0.06
95%	0.27	0.19	0.28	0.25	0.25	0.14	0.27	0.15
				2005-2009				
5%	0.09	0.01	0.00	-0.03	0.00	-0.03	0.00	-0.03
25%	0.04	-0.01	0.04	-0.02	0.05	-0.01	0.05	-0.01
50%	0.09	0.01	0.10	0.01	0.10	0.01	0.10	0.01
75%	0.16	0.03	0.17	0.03	0.16	0.04	0.17	0.04
95%	0.30	0.11	0.36	0.15	0.25	0.12	0.33	0.13

[109] In Bollen (2013) switching model allows exposures to switch once over each fund's history

Panel B: 6 factors

	Standard Normal		T-distr. 1 D.F.		T-distr. 2 D.F.		Bootstrap	
Percentile	Adj.R^2 HL6	Adj.R^2 SGAML6	Adj.R^2 HL6	Adj.R^2 SGAML6	Adj.R^2 HL6	Adj.R^2 SGAML6	Adj.R^2 HL6	Adj.R^2 SGAML6
				1995-1999				
5%	0.00	-0.03	0.00	-0.03	0.00	-0.03	0.00	-0.03
25%	0.00	-0.02	0.00	-0.02	0.00	-0.02	0.00	-0.01
50%	0.04	0.00	0.03	0.01	0.03	0.01	0.03	0.01
75%	0.08	0.02	0.06	0.05	0.07	0.04	0.07	0.05
95%	0.16	0.08	0.17	0.17	0.15	0.10	0.16	0.12
				2000-2004				
5%	0.00	-0.03	0.00	-0.03	0.00	-0.03	0.00	-0.03
25%	0.00	-0.01	0.00	-0.02	0.00	-0.01	0.00	-0.02
50%	0.04	0.01	0.03	0.01	0.03	0.02	0.04	0.01
75%	0.07	0.04	0.06	0.04	0.06	0.04	0.08	0.04
95%	0.16	0.09	0.15	0.15	0.14	0.11	0.16	0.10
				2005-2009				
5%	0.00	-0.03	0.00	-0.03	0.00	-0.03	0.00	-0.03
25%	0.00	-0.02	0.00	-0.03	0.00	-0.03	0.00	-0.03
50%	0.03	-0.01	0.02	-0.01	0.02	-0.01	0.03	-0.01
75%	0.07	0.03	0.06	0.02	0.08	0.03	0.07	0.02
95%	0.13	0.08	0.26	0.20	0.16	0.08	0.15	0.11

Next, the four critical values are applied in classification of funds by form of their risk exposures[110]. Table 7.2 displays the results of the classification of funds into three subsets for every hedge fund category. The three groups consist of funds which show only linear exposures (Linear), funds with nonlinear exposures (Nonlinear), and funds with low or insignificant exposures to systematic risk (None). Panel A shows the results for the 14-factor models, and Panel B for the six-factor models. The table also reports average values of R^2 of the linear and the nonparametric models fitted to individual funds' returns.

The table reveals several important findings. First of all, the nonparametric model is significant roughly in one fund out of five. The proportion of funds in the nonlinear subset is 15% and 21% based on the 14- and six-factor models respectively. These numbers match closely the estimates obtained by Diez de los Rios and Garcia (2011). Diez de los Rios and Garcia (2011) use option pricing methodology to assess option-like effects in risk exposures of individual hedge funds and find support to reject the hypothesis of linearity in one-fifth of

[110] Classification rules are described in Algorithm 5.1 in Section 5.2.1

funds. Thus, the finding confirms that one-fifth of funds participate in complex dynamic trading strategies as their exposures are different from linear exposures induced by buy-and-hold like strategies. It also suggests that significant nonlinear patterns detected at the portfolio level do not apply to all the funds in the style indices.

Secondly, the majority of hedge funds, around 66% or two-thirds, exhibit only linear exposures when the fourteen-factor models are applied. This figure again matches closely the proportion of funds with significant linear exposures reported in the literature. Bollen (2013) finds that for 68.6% of funds linear regressions are statistically significant, while for the remaining 31.4% of funds regressions' R^2 is not significantly different from zero[111]. The estimate of the percentage of linear funds using the six-factor models is 51%, 15% less when the 14-factor models are used. The difference between the estimates might signal the presence of omitted variables in the smaller model. Slightly higher proportion of nonlinear funds based on six-factor models can also be attributed to the problem of omitted variables. Due to its higher flexibility the nonlinear model, perhaps, fits part of the return variation which should be attributed to linear exposures to omitted variables if they were included in the model.

The proportion of funds without any significant exposure to systematic risk is 19% and 28% respectively for the 14- and six-factor models. The latter figure is likely to be overstated due to potentially important factors missing in the six-factor models. Overall, the figures on the proportions of linear, nonlinear funds and funds with insignificant exposures reported in Table 7.2 reconcile the estimates of the number of linear funds given in Bollen (2013) and the number of nonlinear funds in Diez de los Rios and Garcia (2011). Of 31.4% of funds

[111] This numbers correspond to the results from the 14-factor model used in Bollen (2013) .

classified as 'zero R^2' funds in Bollen (2013), around 15-20% actually have significant risk exposures, but these exposures are nonlinear, consistent with the findings of Diez de los Rios and Garcia (2011).

Further examination of Table 7.2 shows some variation of proportions of funds with linear and nonlinear exposures across hedge fund styles. The Convertible Arbitrage category appears to have the highest proportion of nonlinear funds: 26% of funds are classified as nonlinear using the 14-factor models and 34% using the six-factor models. The average R^2 of nonparametric models in this style is 0.31 for the SGAML14 model and 0.27% for the GAML6 model; both numbers are well above the critical values of 0.1684 and 0.1193 indicating that nonlinearities cannot be attributed to noise in the data. The high percentage of nonlinear funds in this category is consistent with earlier arguments about nonlinear payoffs of relative value funds and numerous nonlinear patterns detected in the Convertible Arbitrage style at the portfolio level (see Section 6.2 and Figure 6.3). Nevertheless, along with the large proportion of nonlinear funds there are many linear funds in this style, as well as in other arbitrage related styles (ED, FIA). Around 40-60% of funds in arbitrage styles exhibit only linear exposures. This observation highlights the fact that there is substantial heterogeneity among funds within styles in terms of trading strategies and risk profiles (Brown & Goetzmann, 2003). Also, it leads to the conclusion pointed out by Diez de los Rios and Garcia (2011) that results on hedge fund nonlinearities can be misleading when based only on hedge fund index data.

In general, the variation of the proportion of linear and nonlinear funds among the styles is as expected from earlier results at the portfolio level in Section 6.2: there are more linear funds in directional styles including the Dedicated Short Bias (80% and 77% using the 14-

and six-factor models respectively), the Long-Short Equity (75% and 61%), and the Emerging Markets (74% and 66%) styles. The proportion of funds with nonlinearities in the Long-Short equity style, the largest hedge fund style, is 14% (11% for six-factor models). This value is consistent with the estimates of Diez de los Rios and Garcia (2011) who find 10% to 15% of long-short equity funds having nonlinear risk-return relationships. The styles with the highest proportion of funds without any significant exposures, linear or nonlinear, are the Equity-Market Neutral (37% and 45% using the 14- and six-factor models), the Global Macro (38% and 49%) and the Managed Futures (47% using both types of models) categories, i.e. those categories where multi-factor models traditionally demonstrate poor explanatory power.

In summarizing the results, there is evidence of nonlinearities in individual funds that corroborates the findings of nonlinear patterns documented at the portfolio level. However despite theoretical expectation of nonlinearities, such nonlinearities do not seem to be a characteristic feature of all hedge funds, as their presence is confirmed empirically only in approximately one-fifth of funds.

Table 7.2 Fund Classification by Form of Systematic Risk Exposure

The table shows the number of funds, the proportion of funds and the average linear and nonparametric regression R^2 for linear, nonlinear and funds with insignificant exposures over three sub-periods, 1995-1999, 2000-2004, 2005-2009. The hedge fund styles are: Convertible Arbitrage (CA), Dedicated Short Bias (DSB), Event Driven (ED), Emerging Markets (EM), Equity Market Neutral (EMN), Fixed Income Arbitrage (FIA), Fund of Funds (FoF), Global Macro (GM), Long-Short Equity (LSE), Managed Futures (MF), and Multi-Strategy (MS).

Panel A: 14 factors

Style	Linear				Nonlinear				None			
Year	# Funds	% Funds	Adj R2 SLM14	Adj R2 SGAML14	# Funds	% Funds	Adj R2 SLM14	Adj R2 SGAML14	# Funds	% Funds	Adj R2 SLM14	Adj R2 SGAML14
CA	**62**	**49%**	**0.54**	**0.06**	**33**	**26%**	**0.51**	**0.31**	**31**	**25%**	**0.17**	**0.06**
1995	16	52%	0.45	0.03	5	16%	0.38	0.20	10	32%	0.15	0.05
2000	28	51%	0.50	0.05	6	11%	0.31	0.22	21	38%	0.18	0.07
2005	18	45%	0.67	0.10	22	55%	0.60	0.37	0	0%	0.00	0.00
DSB	**24**	**80%**	**0.70**	**0.05**	**4**	**13%**	**0.75**	**0.22**	**2**	**7%**	**0.23**	**0.00**
1995	5	71%	0.67	0.02	1	14%	0.80	0.20	1	14%	0.24	0.02
2000	12	86%	0.74	0.05	2	14%	0.71	0.21	0	0%	0.00	0.00
2005	7	78%	0.65	0.06	1	11%	0.76	0.28	1	11%	0.23	-0.02
ED	**226**	**60%**	**0.51**	**0.04**	**65**	**17%**	**0.46**	**0.26**	**87**	**23%**	**0.17**	**0.03**
1995	59	75%	0.48	0.04	4	5%	0.53	0.21	16	20%	0.17	0.01
2000	76	53%	0.51	0.04	19	13%	0.34	0.21	48	34%	0.18	0.04
2005	91	58%	0.54	0.05	42	27%	0.51	0.29	23	15%	0.15	0.04
EM	**226**	**74%**	**0.58**	**0.04**	**44**	**14%**	**0.50**	**0.29**	**34**	**11%**	**0.17**	**0.04**
1995	32	80%	0.64	0.05	4	10%	0.58	0.23	4	10%	0.20	0.06
2000	76	79%	0.51	0.04	3	3%	0.38	0.20	17	18%	0.14	0.04
2005	118	70%	0.60	0.04	37	22%	0.50	0.30	13	8%	0.19	0.04
EMN	**77**	**44%**	**0.48**	**0.05**	**32**	**18%**	**0.45**	**0.29**	**65**	**37%**	**0.17**	**0.04**
1995	6	29%	0.40	0.00	0	0%	0.00	0.00	15	71%	0.13	0.03
2000	28	45%	0.45	0.05	11	18%	0.18	0.19	23	37%	0.18	0.04
2005	43	47%	0.51	0.06	21	23%	0.60	0.34	27	30%	0.19	0.03
FIA	**41**	**36%**	**0.42**	**0.06**	**22**	**19%**	**0.39**	**0.35**	**51**	**44%**	**0.15**	**0.04**
1995	8	57%	0.46	0.03	1	7%	0.40	0.17	6	36%	0.12	0.03
2000	14	30%	0.35	0.07	6	13%	0.22	0.20	26	57%	0.14	0.05
2005	19	36%	0.44	0.06	15	28%	0.45	0.43	19	36%	0.18	0.03
FoF	**1643**	**75%**	**0.61**	**0.05**	**318**	**14%**	**0.53**	**0.25**	**237**	**11%**	**0.17**	**0.05**
1995	176	75%	0.62	0.05	31	13%	0.49	0.26	29	12%	0.18	0.04
2000	406	76%	0.53	0.05	59	11%	0.48	0.22	72	13%	0.18	0.05
2005	1061	75%	0.63	0.05	228	16%	0.54	0.26	136	9%	0.16	0.04
GM	**67**	**47%**	**0.51**	**0.04**	**22**	**15%**	**0.32**	**0.27**	**54**	**38%**	**0.17**	**0.04**
1995	12	46%	0.47	0.05	4	15%	0.17	0.31	10	38%	0.17	0.03
2000	27	55%	0.49	0.04	5	10%	0.38	0.27	17	35%	0.19	0.03
2005	28	41%	0.55	0.05	13	19%	0.35	0.26	27	40%	0.16	0.05
LSE	**999**	**75%**	**0.56**	**0.05**	**156**	**12%**	**0.49**	**0.25**	**186**	**14%**	**0.19**	**0.04**
1995	166	87%	0.59	0.03	8	4%	0.48	0.20	17	9%	0.17	0.05
2000	353	77%	0.54	0.06	39	8%	0.47	0.23	69	15%	0.18	0.04
2005	480	70%	0.57	0.05	109	16%	0.50	0.26	100	14%	0.19	0.04
MF	**140**	**31%**	**0.42**	**0.05**	**96**	**21%**	**0.19**	**0.25**	**213**	**47%**	**0.17**	**0.06**
1995	30	31%	0.50	0.05	15	15%	0.21	0.25	52	54%	0.17	0.08
2000	81	52%	0.39	0.05	11	7%	0.26	0.21	65	41%	0.18	0.04
2005	29	15%	0.42	0.04	70	36%	0.17	0.26	96	49%	0.15	0.06
MS	**174**	**54%**	**0.54**	**0.05**	**54**	**17%**	**0.43**	**0.26**	**95**	**29%**	**0.16**	**0.05**
1995	10	42%	0.58	0.04	2	8%	0.72	0.34	12	50%	0.18	0.07
2000	44	46%	0.48	0.05	19	20%	0.30	0.22	33	34%	0.16	0.04
2005	120	59%	0.56	0.05	33	16%	0.48	0.28	50	25%	0.16	0.04
Total	**3679**	**66%**	**0.57**	**0.05**	**846**	**15%**	**0.46**	**0.26**	**1055**	**19%**	**0.17**	**0.05**

Panel B: 6 factors

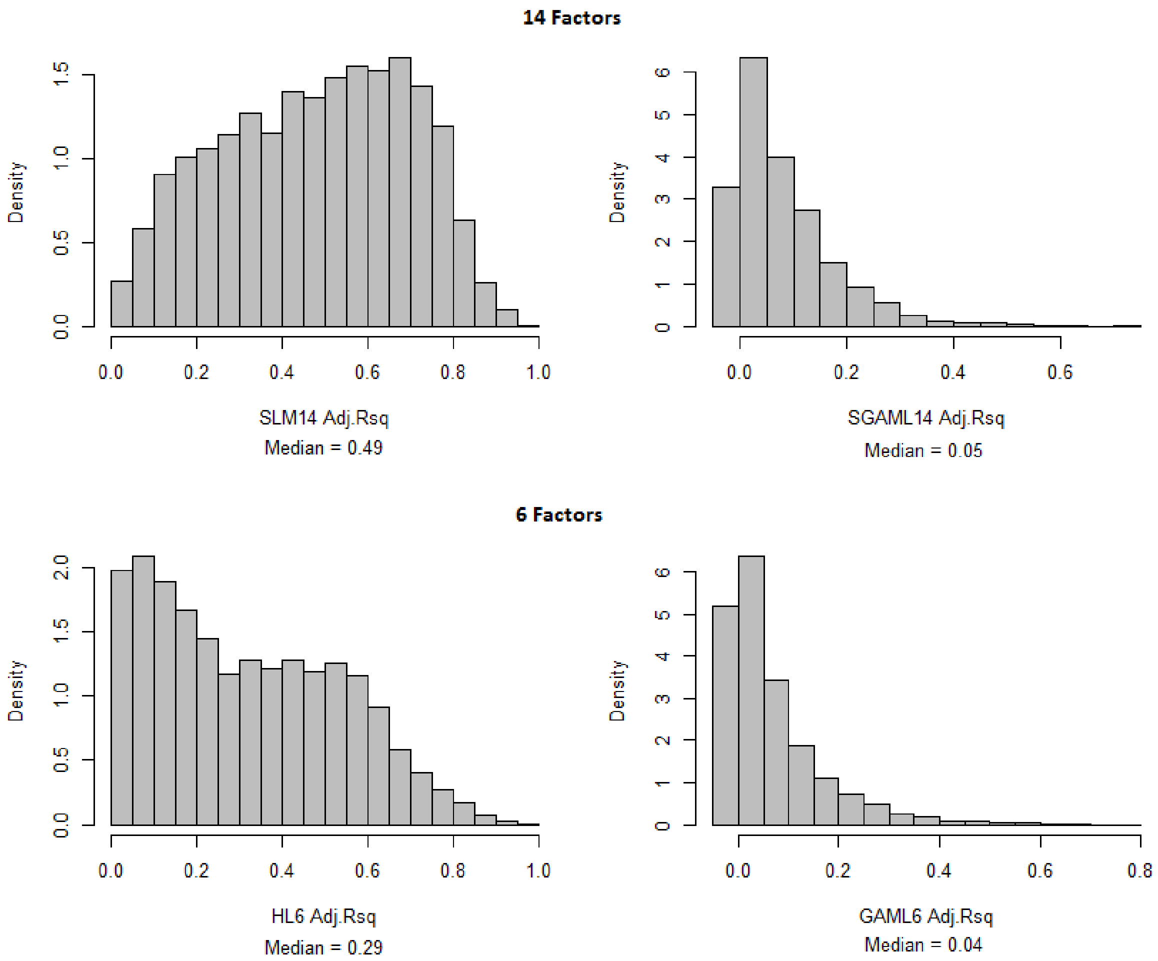
Style	Linear				Nonlinear				None			
Year	# Funds	% Funds	Adj R2 SLM14	Adj R2 SGAML14	# Funds	% Funds	Adj R2 SLM14	Adj R2 SGAML14	# Funds	% Funds	Adj R2 SLM14	Adj R2 SGAML14
CA	**45**	**36%**	**0.40**	**0.04**	**43**	**34%**	**0.45**	**0.27**	**38**	**30%**	**0.09**	**0.04**
1995	9	29%	0.32	0.04	7	23%	0.23	0.15	15	48%	0.09	0.03
2000	25	45%	0.31	0.03	7	13%	0.07	0.15	23	42%	0.09	0.05
2005	11	28%	0.65	0.06	29	73%	0.60	0.33	0	0%	0.00	0.00
DSB	**23**	**77%**	**0.53**	**0.01**	**4**	**13%**	**0.65**	**0.18**	**3**	**10%**	**0.15**	**0.00**
1995	6	86%	0.52	0.02	0	0%	0.00	0.00	1	14%	0.15	0.01
2000	10	71%	0.54	0.01	2	14%	0.65	0.17	2	14%	0.15	-0.01
2005	7	78%	0.52	0.00	2	22%	0.65	0.19	0	0%	0.00	0.00
ED	**190**	**51%**	**0.39**	**0.02**	**90**	**24%**	**0.44**	**0.24**	**98**	**26%**	**0.08**	**0.02**
1995	38	49%	0.36	0.04	26	32%	0.25	0.19	15	18%	0.07	0.03
2000	74	52%	0.32	0.01	2	1%	0.34	0.18	67	46%	0.07	0.02
2005	78	50%	0.46	0.03	62	40%	0.52	0.26	16	10%	0.10	0.04
EM	**200**	**66%**	**0.43**	**0.01**	**49**	**16%**	**0.47**	**0.24**	**55**	**18%**	**0.09**	**0.01**
1995	30	75%	0.37	0.03	7	18%	0.38	0.19	3	8%	0.09	0.00
2000	67	71%	0.35	0.00	2	2%	0.07	0.12	27	27%	0.08	-0.01
2005	103	61%	0.49	0.02	40	24%	0.51	0.26	25	15%	0.10	0.03
EMN	**51**	**30%**	**0.30**	**0.03**	**42**	**24%**	**0.35**	**0.30**	**81**	**45%**	**0.08**	**0.02**
1995	2	11%	0.24	-0.01	1	5%	0.10	0.15	18	84%	0.07	0.02
2000	18	31%	0.21	0.01	3	5%	0.27	0.16	41	64%	0.09	0.02
2005	31	34%	0.36	0.05	38	41%	0.37	0.31	22	24%	0.07	0.03
FIA	**46**	**42%**	**0.32**	**0.04**	**28**	**26%**	**0.31**	**0.28**	**40**	**32%**	**0.08**	**0.04**
1995	10	71%	0.34	0.05	1	7%	0.33	0.19	4	21%	0.03	0.07
2000	19	43%	0.22	0.03	5	11%	0.10	0.15	22	45%	0.09	0.04
2005	17	33%	0.41	0.04	22	43%	0.36	0.31	14	24%	0.08	0.05
FoF	**1099**	**50%**	**0.42**	**0.03**	**616**	**28%**	**0.48**	**0.23**	**483**	**21%**	**0.09**	**0.02**
1995	158	67%	0.44	0.03	41	17%	0.37	0.21	37	15%	0.11	0.03
2000	241	45%	0.31	0.01	27	5%	0.15	0.16	269	50%	0.09	0.01
2005	700	50%	0.46	0.04	548	39%	0.50	0.24	177	12%	0.09	0.03
GM	**47**	**34%**	**0.36**	**0.02**	**26**	**17%**	**0.21**	**0.21**	**70**	**49%**	**0.08**	**0.03**
1995	6	24%	0.33	0.02	4	12%	0.12	0.16	16	64%	0.09	0.04
2000	21	43%	0.35	0.01	6	12%	0.15	0.22	22	45%	0.08	0.02
2005	20	31%	0.38	0.03	16	23%	0.26	0.22	32	46%	0.07	0.03
LSE	**808**	**61%**	**0.42**	**0.02**	**128**	**10%**	**0.40**	**0.19**	**405**	**29%**	**0.08**	**0.02**
1995	138	72%	0.41	0.02	16	8%	0.28	0.16	37	19%	0.10	0.03
2000	227	50%	0.36	0.01	13	3%	0.30	0.15	221	47%	0.08	0.01
2005	443	65%	0.46	0.02	99	15%	0.43	0.20	147	20%	0.08	0.02
MF	**151**	**35%**	**0.31**	**0.03**	**82**	**19%**	**0.15**	**0.19**	**216**	**47%**	**0.08**	**0.03**
1995	29	31%	0.37	0.03	21	22%	0.19	0.18	47	47%	0.08	0.04
2000	93	61%	0.29	0.03	19	13%	0.16	0.18	45	26%	0.10	0.03
2005	29	15%	0.35	0.02	42	22%	0.12	0.20	124	63%	0.08	0.03
MS	**144**	**47%**	**0.41**	**0.02**	**61**	**19%**	**0.44**	**0.23**	**118**	**34%**	**0.07**	**0.02**
1995	8	33%	0.43	0.06	5	21%	0.33	0.26	11	46%	0.10	0.03
2000	36	42%	0.35	0.02	7	6%	0.17	0.15	53	52%	0.06	0.02
2005	100	51%	0.42	0.02	49	25%	0.47	0.23	54	24%	0.07	0.02
Total	**2804**	**51%**	**0.41**	**0.03**	**1169**	**21%**	**0.43**	**0.23**	**1607**	**28%**	**0.08**	**0.02**

Finally, in conclusion to this section, Figure 7.1 presents distributions of R^2 coefficients for the linear and the nonparametric 14- and six-factor models for all individual hedge funds. As seen from the figure distributions of R^2 of the 14- and the six-factor nonparametric models (top and bottom graphs on the right) look quite similar and have a very close median values of 0.05 (SGAML14) and 0.04 (GAML6). The two distributions of linear models' R^2, on the contrary, are very different. The distribution of R^2 of the six-factor HL6 model (bottom left graph) is highly positively skewed, and R^2 for many funds is close to zero; the median value is 0.29. The distribution of R^2 of the 14-factor SLM14 model resembles a normal distribution; its median value is almost twice higher, 0.49. This comparison suggests that the use of the extended set of factors and variable selection procedures is essential, as it leads to substantial improvement in the model performance. As mentioned above, omitted linear exposures can lead to overstatement of nonlinear effects. Thus, the remaining part of this chapter focuses only on the results from the 14-factor models[112].

[112] All the results using the six-factor models are available upon request; qualitatively they are not different from the results based on the14-factor models

Figure 7.1 Distribution of Linear and Residual Nonlinear R^2 in Individual Funds

The figure shows the distributions of the adjusted R^2 coefficient for the linear model SLM14 fitted to the returns of individual hedge funds and the nonlinear model SGAML14 fitted to the residuals of the linear model using three non-overlapping five-year periods: 1995-1999, 2000-2004 and 2005-2009.



7.2 Performance of Funds with Nonlinearities

The next question to be examined is related to the performance analysis of the funds with nonlinear exposures relatively to the funds with linear only and insignificant systematic risk exposures. Different forms of exposures reflect different investment approach. Thus, it is of great interest to investigate whether funds following dynamic and complex strategies resulting in nonlinear payoffs outperform funds following mutual fund-like buy-and-hold directional strategies with linear payoffs and risk-neutral strategies with hedged risk exposures.

Before discussing the results a word of caution is necessary regarding the methodology. After funds are classified equal-weighted portfolios of funds having the same form of exposures (i.e. linear, nonlinear or none) are constructed and their performance is analysed. These portfolios do not produce investable returns due to the look-ahead bias when defining the form of funds' exposures. As will become clear later in this chapter (see Section 7.3) fund's form of exposures shows little persistence; i.e. a fund classified initially as a linear fund has a high chance of changing their form of exposures, moving to linear subset in the next period. Thus, ex-ante performance analysis of subsets of funds is not feasible. Nevertheless, an ex-post comparison of performance of subsets of funds is still very valuable, as it helps to understand the difference between the groups of funds with different risk-return profiles and utilizing different investment approaches.

Table 7.3 shows summary statistics for the three subsets of funds over the period 1995-2009. Funds are classified at the start of the year in 1995, 2000 and 2005 using a 5-year window. There are several notable differences between the subsets. On average monthly return of the nonlinear funds is 0.59%; it is lower than the return of the linear funds, 0.69%, and the return of funds with insignificant exposures, 0.87%. At the same time the nonlinear funds feature higher volatility of 3.67% per month, comparing with 3.46% and 3.01% for the 'Linear' and the 'None' subsets. Moreover, the distribution of nonlinear funds' returns is more negatively skewed and has higher kurtosis than the distributions of the linear funds and the funds with insignificant exposures. The higher values of the skewness and the kurtosis imply excessive exposure to the negative tail risk among the nonlinear funds and provide empirical support to the notion that some of hedge funds act as providers of financial insurance against distress situations. Given that nonlinearities are more pronounced at the boundaries, it is not surprising to find that the nonlinear funds carry higher left tail risk than the linear funds. These results hold among most of the hedge fund styles.

Table 7.3 Descriptive Statistics of Fund Subsets by Form of Systematic Risk Exposure

Listed are the summary statistics of fund subsets during 1995-2009. The subsets are formed from the funds with only linear exposures (Linear), the funds with any nonlinear exposures (Nonlinear) and the funds with low or insignificant exposures (None). The summary statistics are the equal-weighted cross-sectional averages of the number of monthly observations: the mean monthly return (Mean), the standard deviation of monthly returns (SD), the skewness (SKEW), and the kurtosis (KURT).

Style	Exposure	Mean	SD	SKEW	KURT
CA	Linear	0.0089	0.0284	-0.5422	6.9347
	Nonlinear	0.0062	0.0330	-1.7689	13.0078
	None	0.0088	0.0107	-0.2060	4.6306
DSB	Linear	0.0015	0.0693	0.1289	5.6548
	Nonlinear	0.0016	0.0532	-0.8653	8.0217
	None	0.0055	0.0280	0.3868	2.9973
EM	Linear	0.0125	0.0668	-0.2558	5.6881
	Nonlinear	0.0064	0.0502	-1.4194	12.4262
	None	0.0151	0.0420	0.4066	7.9697
EMN	Linear	0.0060	0.0271	-0.2001	5.4624
	Nonlinear	0.0036	0.0262	-1.2065	13.0007
	None	0.0075	0.0251	0.4083	5.6904
ED	Linear	0.0077	0.0271	-0.6560	6.2255
	Nonlinear	0.0053	0.0298	-1.2557	11.4802
	None	0.0093	0.0257	0.1434	6.6340
FIA	Linear	0.0078	0.0288	-0.7753	8.3931
	Nonlinear	0.0057	0.0419	-1.7475	18.3837
	None	0.0071	0.0163	-0.1123	5.2692
GM	Linear	0.0094	0.0443	0.1544	4.8968
	Nonlinear	0.0116	0.0496	0.6884	7.7392
	None	0.0074	0.0340	0.4647	5.3579
LSE	Linear	0.0093	0.0452	-0.0624	5.4513
	Nonlinear	0.0083	0.0474	0.2886	9.4433
	None	0.0093	0.0347	0.1805	6.1891
MF	Linear	0.0094	0.0582	0.0980	4.3075
	Nonlinear	0.0084	0.0611	0.4507	4.9414
	None	0.0097	0.0483	0.1927	4.1626
MS	Linear	0.0062	0.0299	-0.5192	6.1212
	Nonlinear	0.0077	0.0276	-0.3879	10.2804
	None	0.0094	0.0226	0.1724	6.7213
FoF	Linear	0.0042	0.0229	-0.8784	6.3657
	Nonlinear	0.0036	0.0258	-1.2621	11.3150
	None	0.0070	0.0215	-0.0916	6.9907
Overall	Linear	0.0069	0.0346	-0.5019	5.9549
	Nonlinear	0.0059	0.0367	-0.7106	10.4738
	None	0.0087	0.0301	0.1257	5.9526

For better understanding of perforamnce of funds with different forms of risk exposures Table 7.4 displays the results of the performance analysis over the entire sample 1995-2009. As before, funds are classified into the three subsets at the beginning of 1995, 2000 and 2005. The ‘Linear’, the ‘Nonlinear’ and the ‘None’ portoflios are the equal-weighted portfolios of funds formed in 1995 and rebalanced in 2000 and 2005 after the re-classification of funds.

Several observations emerge from the table. The first striking result is related to negative difference between the Sharpe ratios, alphas and the appraisal ratios of the nonlinear and the linear funds across the styles, though it is statistically significant only for alpha and the appraisal ratio at 1% and 5% level repsectively. It means that overall funds with nonlinearities tend to underperform funds with linear risk exposures. The difference between the Sharpe ratios is negative and signficant in four styles out of eleven (EM, ED, LSE, FoF), and positive and significant in one style only (MS). The difference between alpha and the appraisal ratio of the nonlinear and the linear funds is negative and significant in three styles (EM, EMN, ED – appraisal ratio, FoF - alpha) and positive and significant in one style (MS).

In addition to poor performance nonlinear funds exhibit higher negative tail risk, as measured by the expected shortfall. Nonlinear funds overall have higher negative expected shortfall than linear funds and the difference is highly significant at the 1% level. The difference between the expected shortfall of nonlinear and linear funds is negative and significane in six styles out of eleven, and positive and siginificant in none of the style. It confirms the notion that nonlinear features lead to higher negative tail risk among nonlinear funds.

The findings about poor relative performance and higher negative tail risk are very important, because they contribute to the debate about fund manager skill and the value added by hedge funds to investors. In practical terms the whole concept of hedge fund investing can be justified if hedge funds fulfill two conditions. Firstly, the strategies they employ are beyond the capabilites of unsophisticated investors, i.e. they cannot be easily implemented without relying on hedge funds. Secondly, and most importantly, these strategies generate positive incremental value to investors. While the findings in the previous Section 7.1 about the presence of nonlinear features in individual hedge funds seem to suggets that some of hedge funds fulfill the first condition as they follow strategies more complex than buy-and-hold like strategies, there is little evidence in Table 7.4 to support the notion that hedge funds pass the second condition. The results indicate that over the long run hedge funds with more complex trading strategies with nonlinear payoffs exhibit higher left tail risk, but do not generate positive returns relative to the portfolio of funds with more simple strategies with linear risk-return profiles.

These findings are consistent with literature on performance of hedge funds' complex trading strategies. Chen (2011) and Peltomäki (2009) perform a comprehensive comparison of hedge funds which use and do not use derivatives. These studies are relevant because derivatives are one of potential sources of nonlinearities (see Section 3.1.2). Chen (2011) finds that hedge funds derivatives users do not show significantly better performance than nonusers. The study of Peltomäki (2009) yields similar findings. The complexity of derivative strategies of hedge funds is found to be positively related to weaker performance and increased probability of large losses[113].

Another prominent result in Table 7.4 is related to performance of funds with insignificant exposures, i.e. the 'None' subset. In all the styles except the Dedicated Short Bias and the Global Macro categories these funds perform remarkably well comparing with the linear and the nonlinear funds. The difference between the Sharpe ratios of the 'Linear' and the 'None' subsets is positive and highly significant at a 1% level in most of the styles. Altough the result is statistically weaker using alpha and appraisal ratios, three performance measures agree that overall funds with insignificant exposures significantly outperform their linear and nonlinear peers. Little is known about these funds; they require further analysis which is beyond the scope of this thesis. Bollen (2013) documents similar result for 'zero R^2'. Funds with low linear regression R^2 are found to feature lower volatilities, higher Sharpe ratios, and higher alphas than other funds.

[113] There is another study on hedge funds derivatives usage by Aragon and Spencer (2012). The authors come to an opposite conclusion. They find that hedge funds using options deliver higher benchmark-adjusted portfolio returns and lower risk than nonusers. However, this result should be taken with caution, as there is potential bias in their data sample. Information on derivatives usage is extracted from hedge funds' 13F filings. In 13F filings there is no requirement to report short option positions. Thus, the sample does not take into account hedge funds' short call and put option positions. Given the discussion in this thesis about the role of hedge funds as insurance providers and numerous short put option payoffs observed in hedge funds' portfolios, ignoring short positions can lead to significant performance bias. Due to this reason the authors do not emphasize the result.

Table 7.4 Performance Characteristics of Fund Subsets with Different Forms of Systematic Risk Exposures

The table presents performance characteristics of individual funds grouped by form of the exposure to systematic risk from 1995-2009. Funds are initially classified in 1995, and reclassified in 2000 and 2005. The 'Linear' group contains funds with only linear significant risk exposures; the 'Nonlinear' group represent funds with any significant nonlinear exposures; and the 'None' group contains funds with insignificant linear and nonlinear risk exposures. Performance characteristics are based on the equal-weighted cross-sectional averages of the number of monthly observations: the annualized Sharpe ratio (Sharpe); the expected shortfall at 95% confidence level (ES); alpha (Alpha), defined as the return of the fund from particular subset within the style minus the average return of all the funds within the style in that period; the appraisal ratio (Appraisal), defined as alpha divided by standard error of residuals from the regression of the fund return on the average return of all the funds within the style in that period. Also, for each measure the difference between its value for 'nonlinear' ('none') exposure funds and 'linear' exposure funds as well as associated two-sided heteroscedastic t-statistic are given. Values of the difference marked with *, **, and *** are significant at the 10, 5, and 1% levels, respectively.

Style	Exposure	Sharpe	Δ Sharpe	t-stat	ES	Δ ES	t-stat	Alpha	Δ Alpha	t-stat	Appraisal	Δ Appraisal	t-stat
CA	Linear	1.5603			-0.0674			0.0008			-0.0416		
	Nonlinear	1.7060	0.1457	0.1941	-0.1204	-0.053***	-3.1483	0.0001	-0.0006	-0.6295	-0.0880	-0.0465	-0.3830
	None	3.4868	1.9265***	4.4424	-0.0157	0.0517***	6.7037	-0.0006	-0.0014	-1.4797	-0.1372	-0.0956	-1.2123
DSB	Linear	0.0193			-0.1515			-0.0007			-0.0079		
	Nonlinear	0.0420	0.0227	0.1147	-0.1401	0.0113	0.2611	-0.0003	0.0004	0.1041	0.0255	0.0334	0.3321
	None	0.6439	0.6246	1.4444	-0.0453	0.1062***	4.3304	0.0065	0.0072	1.0156	0.2479	0.2558	0.9606
EM	Linear	0.7311			-0.1543			0.0009			-0.0539		
	Nonlinear	0.4277	-0.3034***	-3.3612	-0.1458	0.0085	0.5545	-0.0043	-0.0052***	-3.7525	-0.1670	-0.1131***	-3.1720
	None	1.7437	1.0126***	4.2509	-0.1221	0.0322	0.7865	0.0023	0.0014	0.5389	-0.0682	-0.0143	-0.2345
EMN	Linear	0.8093			-0.0566			0.0002			-0.0350		
	Nonlinear	0.8285	0.0192	0.0797	-0.0879	-0.0314***	-3.0940	-0.0019	-0.0021**	-2.3937	-0.2317	-0.1967**	-2.0849
	None	1.7931	0.9839***	2.9943	-0.0559	0.0006	0.0302	-0.0003	-0.0005	-0.4719	-0.0915	-0.0566	-0.7946
ED	Linear	1.3882			-0.0645			-0.0001			-0.0390		
	Nonlinear	0.8486	-0.5397***	-3.8406	-0.0886	-0.024***	-2.6669	-0.0011	-0.0010	-1.5471	-0.1160	-0.0771**	-2.6024
	None	2.1688	0.7805***	3.7196	-0.0407	0.0238***	3.9793	0.0010	0.0012	0.9818	0.0074	0.0464	0.9498
FIA	Linear	1.5528			-0.0699			0.0006			-0.0154		
	Nonlinear	1.3636	-0.1892	-0.3900	-0.1171	-0.0473	-1.5729	0.0000	-0.0006	-0.3549	-0.1948	-0.1794	-1.2254
	None	2.9300	1.3772***	2.7825	-0.0436	0.0263*	1.7002	-0.0004	-0.0009	-0.9870	-0.1652	-0.1499	-1.6032

Contd.

Style	Exposure	Sharpe	Δ Sharpe	t-stat	ES	Δ ES	t-stat	Alpha	Δ Alpha	t-stat	Appraisal	Δ Appraisal	t-stat
GM	Linear	0.7654			-0.0876			0.0003			-0.0241		
	Nonlinear	0.7930	0.0276	0.2383	-0.0957	-0.0081	-0.5445	0.0027	0.0024	1.2679	0.0381	0.0622	1.5668
	None	0.8577	0.0923	0.7697	-0.0599	0.0277***	3.5567	-0.0016	-0.0019*	-1.6647	-0.0651	-0.0410	-1.1816
LSE	Linear	0.8058			-0.0945			0.0001			-0.0237		
	Nonlinear	0.6713	-0.1345***	-2.6488	-0.1240	-0.0295***	-3.6173	0.0001	0.0001	0.1237	-0.0257	-0.0020	-0.1387
	None	1.1899	0.3841***	5.0257	-0.0722	0.0223**	2.5110	0.0007	0.0007	1.2360	-0.0276	-0.0039	-0.2066
MF	Linear	0.8184			-0.1187			-0.0006			-0.0264		
	Nonlinear	0.6967	-0.1217	-0.4978	-0.1137	0.0050	0.4334	-0.0006	0.0000	-0.0113	-0.0489	-0.0224	-0.7579
	None	1.2995	0.481*	1.7554	-0.0947	0.024**	2.1139	0.0003	0.0009	1.1601	0.0252	0.0517*	1.6900
MS	Linear	1.2086			-0.0693			-0.0010			-0.0566		
	Nonlinear	1.7086	0.5001*	1.8014	-0.0658	0.0035	0.3771	0.0005	0.0015**	2.0098	0.0464	0.1029**	2.0842
	None	3.9384	2.7299***	5.4145	-0.0588	0.0105	0.9454	0.0020	0.003***	3.0319	0.3576	0.4142***	5.4486
FoF	Linear	0.8486			-0.0561			-0.0001			-0.0171		
	Nonlinear	0.7262	-0.1224*	-1.7182	-0.0693	-0.0132***	-4.8699	-0.0006	-0.0005*	-1.8835	-0.0320	-0.0149	-0.8332
	None	3.2348	2.3861***	7.7328	-0.0477	0.0084*	1.8899	0.0022	0.0023***	4.6476	0.3426	0.3597***	3.2430
Overall	Linear	0.8933			-0.0778			0.0000			-0.0257		
	Nonlinear	0.8260	-0.0673	-1.2654	-0.0943	-0.0165***	-5.8673	-0.0006	-0.0005**	-2.3686	-0.0519	-0.0262**	-2.3337
	None	2.1915	1.2982***	12.0570	-0.0638	0.014***	4.0555	0.0009	0.0009***	3.6563	0.0819	0.1076***	3.7854

The next Table 7.5 reports the results of the performance analysis separately for three sub-periods. The results for the period 1995-1999 are presented in Panel A, for 2000-2004 in Panel B, and for 2005-2009 in Panel C. During 1995-1999 and 2005-2009 the results are qualitatively similar to those observed in Table 7.4 for the entire sample. Nonlinear funds on average performed worse than linear funds in terms of lower risk-adjusted performance and higher left tail risk. Funds with insignificant exposures outperformed both linear and nonlinear funds. These results confirm the findings for the whole sample period that nonlinear trading strategies of hedge funds do not result in superior performance.

However, in 2000-2004 the nonlinear funds delivered higher Sharpe ratios than the linear funds, but lower ratios than the funds with insignificant exposures. The other three measures (alpha, appraisal ratio and ES) were not significantly different between the nonlinear and the linear funds in that period.

The difference between the sub-periods (i.e. inferior performance of nonlinear funds during 1995-1999 and 2005-2009 and superior performance during 2000-2004) perhaps can be attributed to the market conditions during this times. During the first sub-period the Russian financial crisis affected most arbitrage hedge fund strategies, which are known to have more nonlinearities than other hedge fund styles. This is because the Russian default on government bonds triggered a flight to quality in the bond markets, leading to a dramatic increase in bond spreads, which then expedited the subsequent collapse of the LTCM fund and lead to large losses in the relative value arbitrage funds (Jaeger, 2008). The subprime crisis of 2007-2008 was also a catastrophic period for hedge funds. Most of the hedge fund strategies posted strong negative returns in 2008[114]. However, hedge funds with

[114] Authors calculations based on BarclayHedge data on hedge fund style performance

nonlinearities suffered more than linear funds, because of excessive negative tail risk (see graphs in Figure 7.3 further).

In contrast, during the period 2000-2004, the dot-com crisis in early 2000s hit most equity oriented funds that had primarily linear exposures, than nonlinear funds following relative value arbitrage strategies (see, Figure 7.3). Different market environments provide a plausible explanation of variation in results on relative performance of linear and nonlinear funds across the sub-periods.

The results of performance analysis based classification using six-factor models are reported in Appendix VIII. All the results described above hold in this case as well. On average nonlinear funds are inferior to linear funds and funds with insignificant exposures demonstrate the best performance.

Table 7.5 Performance Characteristics of Funds with Different Forms of Exposure to Systematic Risk over Sub-Periods

The tables present performance characteristics of individual funds sorted by style and form of risk exposures during three periods: 1995-1999, 2000-2004 and 2005-2009.

Panel A: 1995-1999

							1995-1999						
Style	**Exposure**	**Sharpe**	**Δ Sharpe**	**t-stat**	**ES**	**Δ ES**	**t-stat**	**Alpha**	**Δ Alpha**	**t-stat**	**Appraisal**	**Δ Appraisal**	**t-stat**
CA	Linear	2.7858			-0.0421			-0.0006			-0.3352		
	Nonlinear	2.2829	-0.5029	-0.6982	-0.1171	-0.0750	-1.3718	0.0038	0.0044	1.7223	0.1605	0.4957**	2.5114
	None	4.6577	1.8719***	3.2150	-0.0118	0.0303**	2.3309	-0.0009	-0.0002	-0.1758	-0.1449	0.1904	0.9528
DSB	Linear	-0.3679			-0.1219			-0.0043			-0.0007		
	Nonlinear	N/A			N/A			N/A			N/A		
	None	N/A			N/A			N/A			N/A		
EM	Linear	0.1770			-0.2323			0.0011			-0.0179		
	Nonlinear	0.1210	-2.6649	-0.1929	-0.2720	-0.2298	-0.6741	-0.0070	-0.0063	-0.9742	-0.0914	0.2438	-0.6375
	None	0.6783	-2.1075	1.2995	-0.1625	-0.1204**	2.4453	0.0028	0.0035	0.2359	0.0176	0.3529	0.2756
EMN	Linear	1.7910			-0.0486			0.0032			0.0694		
	Nonlinear	N/A			N/A			N/A			N/A		
	None	2.7585	0.9675	0.9763	-0.0967	-0.0481	-0.7468	-0.0011	-0.0042	-1.5621	-0.2647	-0.3342	-1.5857
ED	Linear	2.4007			-0.0569			-0.0009			-0.1380		
	Nonlinear	1.3894	-1.3965	-1.5652	-0.2011	-0.1589	-1.8498	0.0018	0.0024	0.6983	-0.0089	0.3263	1.2625
	None	2.7620	-0.0238	0.7576	-0.0379	0.0042*	1.9566	0.0029	0.0036	1.4678	0.0358	0.371*	1.8730
FIA	Linear	2.7771			-0.0625			0.0010			0.0813		
	Nonlinear	N/A			N/A			N/A			N/A		
	None	4.5797		0.8423	-0.1560		-0.8804	-0.0008		-0.6654	-0.2204		-0.8413
GM	Linear	0.7835			-0.1094			0.0008			-0.0080		
	Nonlinear	0.9065	-1.8793	0.6779	-0.1660	-0.1239	-1.0805	0.0085	0.0091	1.0741	0.1214	0.4567	1.3139
	None	0.8000	-1.9858	0.0692	-0.0554	-0.0133**	2.6118	-0.0049	-0.0043**	-2.3349	-0.1828	0.1524**	-2.5341
LSE	Linear	1.4790			-0.1003			0.0002			-0.0316		
	Nonlinear	1.0334	-1.7525*	-1.9526	-0.1674	-0.1252	-1.6216	-0.0016	-0.0009	-0.3203	-0.0049	0.3304	0.3859
	None	1.9056	-0.8802	0.7932	-0.1759	-0.1338	-1.1051	-0.0011	-0.0004	-0.5393	-0.2383	0.0969	-1.7269
MF	Linear	0.5727			-0.1496			-0.0019			-0.0452		
	Nonlinear	0.7670	-2.0188	1.2524	-0.1315	-0.0894	0.5781	0.0023	0.0029	1.6289	0.0286	0.3639	1.5044
	None	0.6919	-2.0940	0.7237	-0.1192	-0.0771	1.1720	0.0005	0.0011	1.0114	-0.0328	0.3024	0.2808
MS	Linear	2.6705			-0.0713			0.0002			-0.1318		
	Nonlinear	1.3437	-1.4421**	-2.2872	-0.1518	-0.1096	-0.8125	-0.0002	0.0005	-0.2163	-0.0236	0.3116	1.1426
	None	3.7410	0.9551	1.1602	-0.0217	0.0204**	2.5664	-0.0004	0.0003	-0.2662	-0.1508	0.1844	-0.1447
FoF	Linear	1.5272			-0.0719			0.0011			0.0585		
	Nonlinear	0.8869	-1.8989***	-3.5905	-0.0868	-0.0447	-0.9620	-0.0037	-0.003***	-3.7942	-0.1209	0.2143***	-3.9728
	None	1.6292	-1.1566	0.2687	-0.0607	-0.0186	0.8735	-0.0038	-0.0032***	-3.0462	-0.2439	0.0913***	-2.8610
Overall	Linear	1.5212			-0.0936			0.0003			-0.0212		
	Nonlinear	1.0588	-0.4623***	-2.9035	-0.1335	-0.0399***	-3.1397	-0.0007	-0.0010	-0.8688	-0.0464	-0.0252	-0.8074
	None	1.9864	0.4652**	2.3206	-0.0886	0.0050	0.4387	-0.0007	-0.0010	-1.3195	-0.1299	-0.1087***	-2.8557

Panel B: 2000-2004

							2000-2004						
Style	**Exposure**	**Sharpe**	**Δ Sharpe**	**t-stat**	**ES**	**Δ ES**	**t-stat**	**Alpha**	**Δ Alpha**	**t-stat**	**Appraisal**	**Δ Appraisal**	**t-stat**
CA	Linear	1.6986			-0.0431			0.0008			-0.0622		
	Nonlinear	5.5458	3.8472	1.1733	-0.0147	0.0284***	3.2372	-0.0021	-0.0029*	-1.7298	-0.6015	-0.5393	-1.1288
	None	2.9906	1.292**	2.4817	-0.0171	0.026***	3.2860	-0.0005	-0.0013	-0.9504	-0.1543	-0.0922	-0.8784
DSB	Linear	0.1169			-0.1886			0.0006			0.0040		
	Nonlinear	N/A			N/A			N/A			N/A		
	None	N/A			N/A			N/A			N/A		
EM	Linear	1.0374			-0.1118			-0.0004			-0.1047		
	Nonlinear	0.8904	-0.1470	-0.4162	-0.1555	-0.0437	-0.6162	0.0000	0.0004	0.1506	-0.0325	0.0722	1.1877
	None	2.1198	1.0823***	3.1075	-0.1434	-0.0316	-0.4745	0.0022	0.0026	0.6557	-0.1375	-0.0329	-0.3505
EMN	Linear	1.0286			-0.0509			0.0005			-0.0516		
	Nonlinear	1.9672	0.9386*	2.0448	-0.0562	-0.0053	-0.3167	-0.0006	-0.0011	-0.6969	-0.4762	-0.4245	-1.3646
	None	1.8854	0.8568**	2.4313	-0.0380	0.0128	1.1481	-0.0005	-0.0010	-0.6184	-0.0495	0.0022	0.0344
ED	Linear	1.8657			-0.0423			0.0007			-0.0084		
	Nonlinear	1.8719	0.0062	0.0279	-0.0467	-0.0044	-0.3052	-0.0004	-0.0011	-1.0622	-0.1672	-0.1587**	-2.3630
	None	1.9869	0.1212	0.4084	-0.0430	-0.0007	-0.0796	-0.0015	-0.0022	-1.1922	-0.1345	-0.1261*	-1.7062
FIA	Linear	1.7551			-0.0645			0.0015			-0.0734		
	Nonlinear	2.9531	1.1980	1.1029	-0.0372	0.0273	1.1128	-0.0036	-0.0051*	-1.9117	-0.6582	-0.5847	-1.4041
	None	3.6306	1.8755***	3.2145	-0.0194	0.0451***	2.8887	0.0000	-0.0015	-0.9886	-0.1839	-0.1105	-0.6330
GM	Linear	0.9149			-0.0744			0.0003			0.0002		
	Nonlinear	0.6386	-0.2764	-1.1382	-0.0819	-0.0075	-0.3886	0.0000	-0.0003	-0.1609	0.0044	0.0042	0.0777
	None	0.9793	0.0643	0.2860	-0.0567	0.0177	1.5285	-0.0007	-0.0010	-0.6555	-0.0221	-0.0223	-0.4209
LSE	Linear	0.7234			-0.0956			-0.0003			-0.0287		
	Nonlinear	0.8455	0.1222	1.0160	-0.1404	-0.0447**	-2.6181	0.0007	0.0010	0.7762	-0.0138	0.0150	0.4971
	None	1.2394	0.5161***	4.7560	-0.0730	0.0226**	2.1409	0.0013	0.0016*	1.7802	-0.0311	-0.0024	-0.0800
MF	Linear	0.7620			-0.1143			0.0001			-0.0264		
	Nonlinear	2.0344	1.2723	1.0457	-0.0889	0.0254	1.6230	0.0002	0.0001	0.0558	-0.0834	-0.0570	-0.5620
	None	2.6197	1.8577**	2.3470	-0.1059	0.0084	0.4913	-0.0002	-0.0003	-0.2286	0.1164	0.1428*	1.9394
MS	Linear	1.6883			-0.0445			-0.0004			-0.0884		
	Nonlinear	2.2748	0.5865*	1.8452	-0.0489	-0.0044	-0.2439	0.0010	0.0013	1.5683	0.0579	0.1463***	2.8502
	None	2.7918	1.1035	1.6506	-0.0533	-0.0088	-0.6405	-0.0003	0.0001	0.0377	0.1622	0.2506**	2.1937
FoF	Linear	1.6542			-0.0375			-0.0003			-0.0432		
	Nonlinear	1.9111	0.2570	1.5577	-0.0394	-0.0019	-0.3845	0.0008	0.001**	2.0560	0.0180	0.0612*	1.6920
	None	3.5307	1.8766***	3.0204	-0.0369	0.0006	0.0752	0.0009	0.0012	1.6522	0.1873	0.2305*	1.8235
Overall	Linear	1.2347			-0.0697			-0.0001			-0.0405		
	Nonlinear	1.7973	0.5626***	3.4937	-0.0704	-0.0007	-0.1158	0.0003	0.0004	0.8542	-0.0790	-0.0385	-1.1943
	None	2.4266	1.1919***	6.0148	-0.0608	0.0089	1.6465	0.0002	0.0003	0.6356	0.0110	0.0515	1.6040

Panel C: 2005-2009

		2005-2009											
Style	**Exposure**	**Sharpe**	**Δ Sharpe**	**t-stat**	**ES**	**Δ ES**	**t-stat**	**Alpha**	**Δ Alpha**	**t-stat**	**Appraisal**	**Δ Appraisal**	**t-stat**
CA	Linear	0.4206			-0.1160			-0.0001			0.0039		
	Nonlinear	0.4122	-0.0084	-0.0659	-0.1532	-0.0372*	-1.9568	0.0001	0.0002	0.1232	0.0150	0.0111	0.1504
	None	N/A			N/A			N/A			N/A		
DSB	Linear	0.1533			-0.0860			0.0002			0.0031		
	Nonlinear	N/A			N/A			N/A			N/A		
	None	N/A			N/A			N/A			N/A		
EM	Linear	0.6324			-0.1602			0.0014			-0.0238		
	Nonlinear	0.4472	-0.1853**	-2.0690	-0.1239	0.0363***	2.7079	-0.0044	-0.0058***	-4.8994	-0.1942	-0.1704***	-4.4356
	None	1.3944	0.762**	3.1911	-0.0592	0.1011***	4.9401	0.0022	0.0008	0.2768	0.0434	0.0672	0.8848
EMN	Linear	0.6281			-0.0630			0.0000			-0.0216		
	Nonlinear	0.2356	-0.3925***	-2.6819	-0.1027	-0.0396***	-3.7993	-0.0023	-0.0023**	-2.2289	-0.1436	-0.122**	-2.3243
	None	0.9839	0.3558	1.5286	-0.0403	0.0227***	2.9791	0.0029	0.0029	1.0053	0.0216	0.0432	0.7639
ED	Linear	0.6599			-0.0806			-0.0001			-0.0069		
	Nonlinear	0.3199	-0.3401***	-3.8220	-0.0986	-0.0181**	-2.0115	-0.0017	-0.0017**	-2.0408	-0.1002	-0.0933***	-3.1879
	None	2.1682	1.5083***	5.3212	-0.0348	0.0458***	5.5891	0.0042	0.0043***	4.7661	0.2612	0.2681***	5.2486
FIA	Linear	0.8814			-0.0751			-0.0005			-0.0022		
	Nonlinear	0.6848	-0.1966	-0.4625	-0.1481	-0.0729*	-1.9148	0.0013	0.0018	0.8122	-0.0085	-0.0063	-0.0651
	None	1.9271	1.0457	1.2975	-0.0475	0.0277	1.4624	-0.0008	-0.0003	-0.2059	-0.1516	-0.1494	-1.5925
GM	Linear	0.7025			-0.0890			0.0002			-0.0489		
	Nonlinear	0.8245	0.1221	0.7856	-0.0790	0.0100	0.7040	0.0016	0.0014	0.6059	0.0211	0.0700	1.2830
	None	0.8285	0.1260	0.8350	-0.0602	0.0288**	2.4657	-0.0011	-0.0013	-0.7490	-0.0582	-0.0093	-0.1994
LSE	Linear	0.6551			-0.0931			-0.0002			-0.0297		
	Nonlinear	0.5849	-0.0702	-1.3815	-0.1091	-0.016**	-2.1012	0.0002	0.0004	0.7486	-0.0333	-0.0036	-0.2122
	None	1.0894	0.4344***	5.4491	-0.0531	0.04***	8.0494	0.0009	0.0011	1.3840	-0.0104	0.0193	0.8607
MF	Linear	1.4970			-0.0941			0.0003			0.0121		
	Nonlinear	0.3724	-1.1246**	-2.5848	-0.1138	-0.0197	-1.3671	-0.0012	-0.0015	-1.4051	-0.0540	-0.0661	-1.3474
	None	1.4153	-0.0818	-0.1536	-0.0843	0.0098	0.6866	0.0009	0.0006	0.5554	0.0464	0.0343	0.6381
MS	Linear	0.9470			-0.0792			-0.0013			-0.0475		
	Nonlinear	1.3750	0.4280	1.0818	-0.0739	0.0053	0.5857	0.0003	0.0016	1.5544	0.0451	0.0926	1.2840
	None	4.4858	3.5389***	5.3515	-0.0641	0.0150	1.0174	0.0033	0.0046***	4.7189	0.4903	0.5379***	5.9372
FoF	Linear	0.5444			-0.0580			-0.0003			-0.0223		
	Nonlinear	0.4465	-0.0979	-1.3745	-0.0738	-0.0157***	-5.8795	-0.0007	-0.0004	-1.5597	-0.0388	-0.0165	-0.7937
	None	3.9087	3.3643***	7.2871	-0.0541	0.0039	0.6336	0.0042	0.0044***	7.3543	0.6026	0.6249***	3.6482
Overall	Linear	0.6290			-0.0768			-0.0002			-0.0241		
	Nonlinear	0.5161	-0.1129***	-2.5982	-0.0954	-0.0186***	-6.7120	-0.0007	-0.0006**	-2.5374	-0.0474	-0.0233**	-1.9803
	None	2.3398	1.7109***	9.8462	-0.0597	0.0171***	5.6751	0.0021	0.0023***	6.7644	0.2261	0.2502***	5.0396

Figure 7.2 provides further evidence on performance of fund subsets. It displays the graphs of cumulative performance of equal-weighted portfolios of funds with linear, nonlinear and insignificant systematic risk exposures over the period 1995-2009. The graphs [115] demonstrate that the aggregate portfolio of nonlinear funds (see the 'Overall' graph) underperforms the portfolio of linear funds and funds with insignificant exposures. In four styles out of nine (EM, EMN, FIA, and FoF) nonlinear funds generate substantially lower cumulative return over the entire 15-year period. In another four styles (CA, ED, LSE, MS) cumulative returns of linear and nonlinear portfolios are quite close. Only global macro nonlinear funds exhibit substantially higher cumulative returns compared with the linear funds and funds with insignificant exposures. The results confirm the findings about poor relative performance of nonlinear funds.

Next, Figure 7.3 presents cumulative performance graphs separately for each sub-period. Graphs on the left-hand side correspond to performances during the 1995-1999 period, graphs in the middle – the 2000-2004 period, and graphs on the right-hand side – the 2005-2009 period (see the timeline under the graphs). As seen from the graphs in equity oriented styles including the Long-Short equity and the Emerging Markets[116] styles as well as the Fund of Funds category the nonlinear funds outperformed the linear funds during bull market conditions in 2000-2004, and underperformed or trailed the linear funds during the two other periods, in 1995-1999 and 2005-2009. The nonlinear funds from arbitrage styles including the Convertible Arbitrage, the Event Driven and the Fixed Income Arbitrage

[115] In graphs for the Convertible Arbitrage and the Dedicated Short Bias styles the charts for funds with insignificant exposures are missing due to the insufficient data at certain years.

[116] Another equity oriented style, the Dedicated Short Bias, is not examined here, because it has very few nonlinear funds, as seen from Table 7.2.

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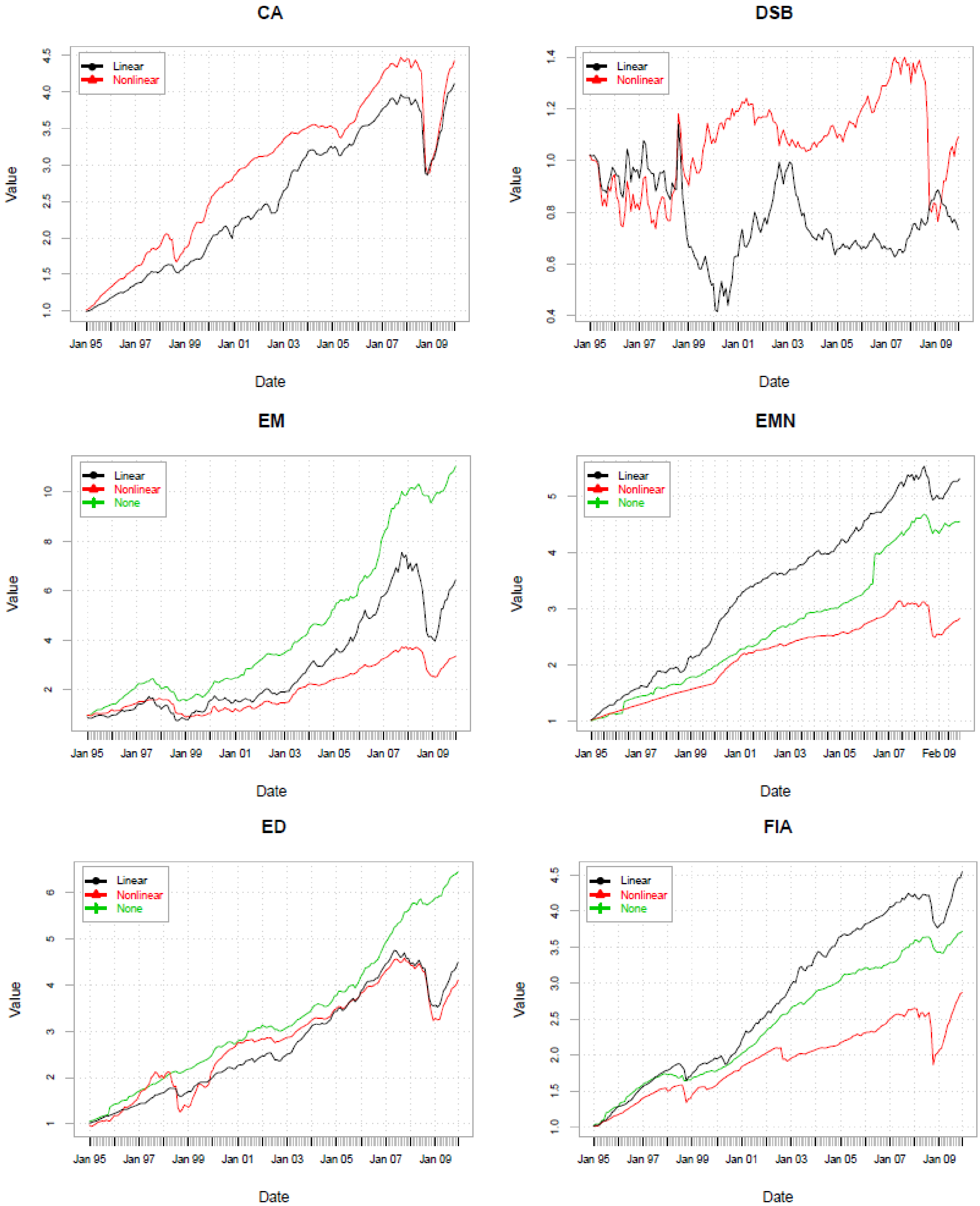
categories clearly suffered more severe losses during the GFC period than the linear funds. Relative performance of the nonlinear funds from these styles in other periods was mixed. The aggregate portfolio of nonlinear funds performed well during 2000-2004 and slightly underperformed linear funds in other periods. Overall, the results are equivalent to those in Table 7.5 and the variation in sub-periods is consistent with the explanation above about the market conditions in these periods which affected the performance of the linear and the nonlinear funds.

Figure 7.2 Cumulative Performance of Equal-Weighted Portfolios of Funds with Different Forms of Exposure to Systematic Risk

The figure shows the cumulative performance of equal-weighted portfolios of funds grouped by the form of fund's exposure to systematic risk over 1995-2009. Funds and initially classified in 1995 and reclassified in 2000 and 2005.




GM
LSE
MF
MS
FoF
Overall
Linear
Nonlinear
None
Value
Date
Jan 95
Jan 97
Jan 99
Jan 01
Jan 03
Jan 05
Jan 07
Jan 09

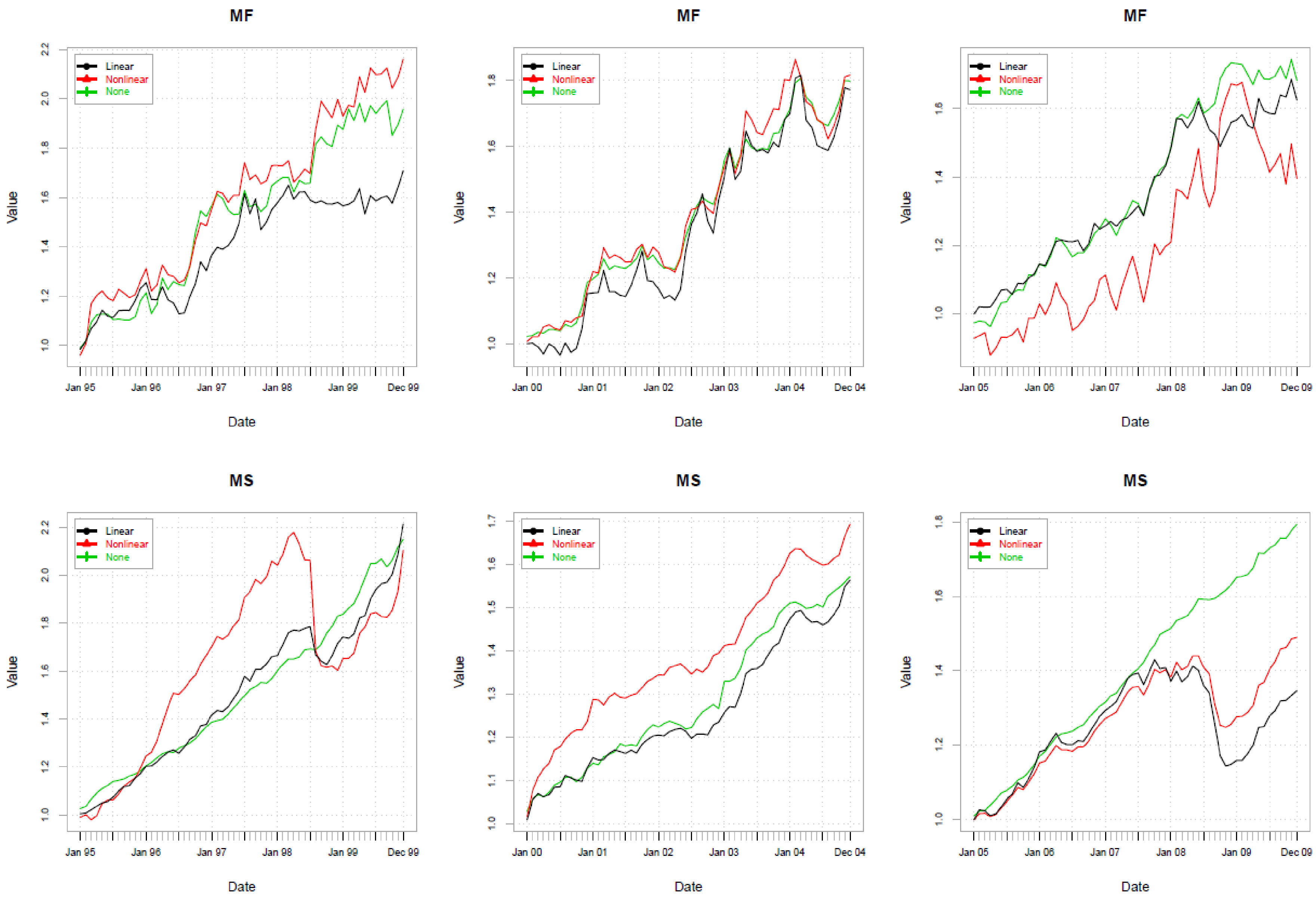
Figure 7.3 Cumulative Performance of Equal-Weighted Portfolios of Funds with Different Form of Exposure to Systematic Risk over Sub-Periods

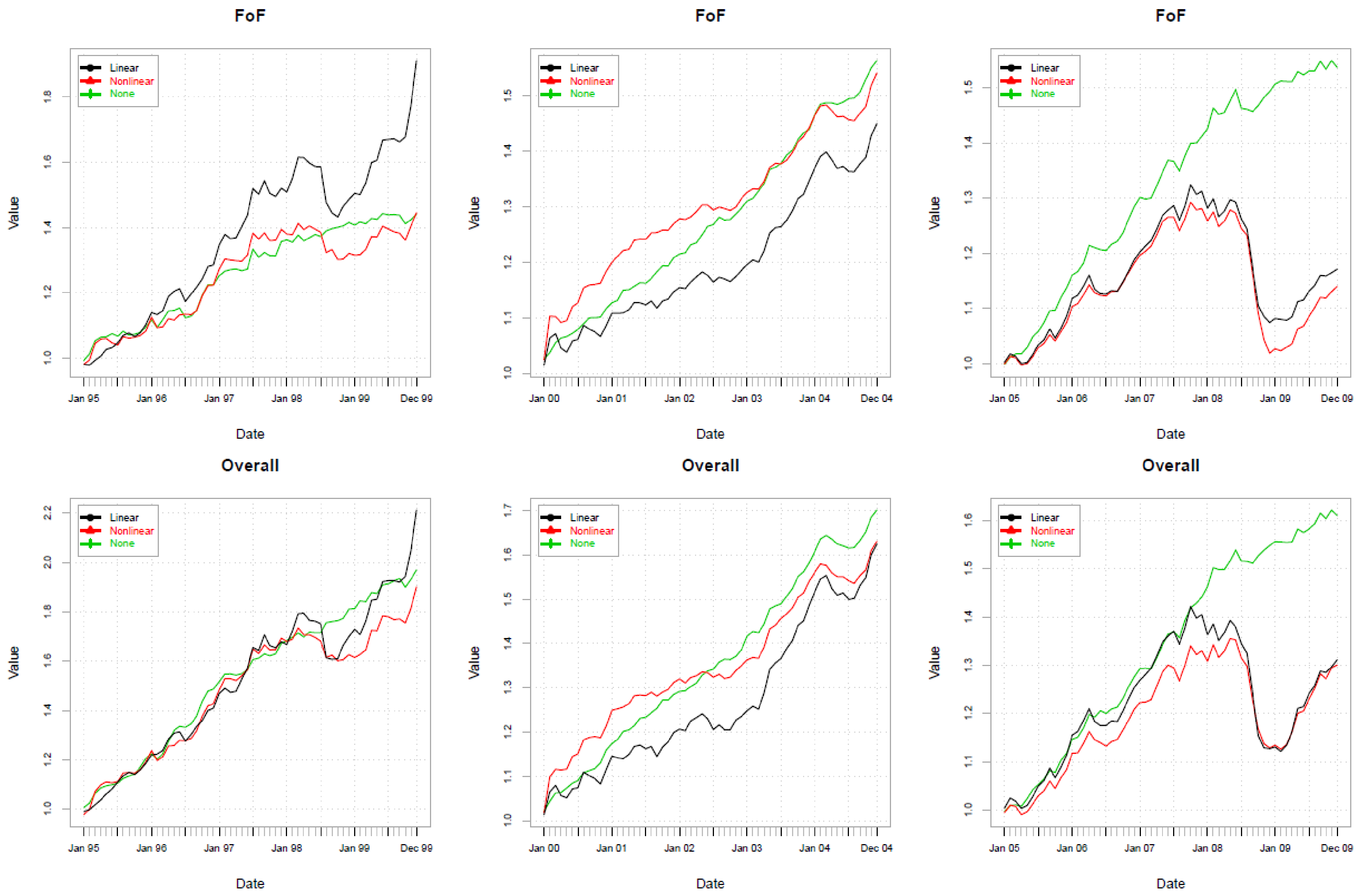
The figure shows cumulative performance of equal-weighted portfolios of funds grouped by form of exposure to systematic risk over three periods: 1995-1999 (graph on the left-hand side), 2000-2004 (graph in the middle) and 2005-2009 (graph on the right-hand side).

EM
Linear
Nonlinear
None
Value
Date
Jan 95
Jan 96
Jan 97
Jan 98
Jan 99
Dec 99
EM
Linear
Nonlinear
None
Value
Date
Jan 00
Jan 01
Jan 02
Jan 03
Jan 04
Dec 04
EM
Linear
Nonlinear
None
Value
Date
Jan 05
Jan 06
Jan 07
Jan 08
Jan 09
Dec 09
EMN
Linear
Nonlinear
None
Value
Date
Jan 95
Jan 96
Jan 97
Jan 98
Jan 99
Dec 99
EMN
Linear
Nonlinear
None
Value
Date
Jan 00
Jan 01
Jan 02
Jan 03
Jan 04
Dec 04
EMN
Linear
Nonlinear
None
Value
Date
Jan 05
Jan 06
Jan 07
Jan 08
Feb 09


ED
ED
ED
FIA
FIA
FIA
Linear
Nonlinear
None
Value
Date
Jan 95
Jan 96
Jan 97
Jan 98
Jan 99
Dec 99
Jan 00
Jan 01
Jan 02
Jan 03
Jan 04
Dec 04
Jan 05
Jan 06
Jan 07
Jan 08
Jan 09
Dec 09

GM
Linear
Nonlinear
None
Value
Date
Jan 95
Jan 96
Jan 97
Jan 98
Jan 99
Dec 99
GM
Linear
Nonlinear
None
Value
Date
Jan 00
Jan 01
Jan 02
Jan 03
Jan 04
Dec 04
GM
Linear
Nonlinear
None
Value
Date
Jan 05
Jan 06
Jan 07
Jan 08
Jan 09
Dec 09
LSE
Linear
Nonlinear
None
Value
Date
Jan 95
Jan 96
Jan 97
Jan 98
Jan 99
Dec 99
LSE
Linear
Nonlinear
None
Value
Date
Jan 00
Jan 01
Jan 02
Jan 03
Jan 04
Dec 04
LSE
Linear
Nonlinear
None
Value
Date
Jan 05
Jan 06
Jan 07
Jan 08
Jan 09
Dec 09


MF
Linear
Nonlinear
None
Value
Date
Jan 95
Jan 96
Jan 97
Jan 98
Jan 99
Dec 99
MF
Linear
Nonlinear
None
Value
Date
Jan 00
Jan 01
Jan 02
Jan 03
Jan 04
Dec 04
MF
Linear
Nonlinear
None
Value
Date
Jan 05
Jan 06
Jan 07
Jan 08
Jan 09
Dec 09
MS
Linear
Nonlinear
None
Value
Date
Jan 95
Jan 96
Jan 97
Jan 98
Jan 99
Dec 99
MS
Linear
Nonlinear
None
Value
Date
Jan 00
Jan 01
Jan 02
Jan 03
Jan 04
Dec 04
MS
Linear
Nonlinear
None
Value
Date
Jan 05
Jan 06
Jan 07
Jan 08
Jan 09
Dec 09


FoF
Linear
Nonlinear
None
Value
Date
Jan 95
Jan 96
Jan 97
Jan 98
Jan 99
Dec 99
1.0
1.2
1.4
1.6
1.8
FoF
Linear
Nonlinear
None
Value
Date
Jan 00
Jan 01
Jan 02
Jan 03
Jan 04
Dec 04
1.0
1.1
1.2
1.3
1.4
1.5
FoF
Linear
Nonlinear
None
Value
Date
Jan 05
Jan 06
Jan 07
Jan 08
Jan 09
Dec 09
1.0
1.1
1.2
1.3
1.4
1.5
Overall
Linear
Nonlinear
None
Value
Date
Jan 95
Jan 96
Jan 97
Jan 98
Jan 99
Dec 99
1.0
1.2
1.4
1.6
1.8
2.0
2.2
Overall
Linear
Nonlinear
None
Value
Date
Jan 00
Jan 01
Jan 02
Jan 03
Jan 04
Dec 04
1.0
1.1
1.2
1.3
1.4
1.5
1.6
1.7
Overall
Linear
Nonlinear
None
Value
Date
Jan 05
Jan 06
Jan 07
Jan 08
Jan 09
Dec 09
1.0
1.1
1.2
1.3
1.4
1.5
1.6

7.3 Persistence of Form of Fund's Exposures

The findings reported in the previous section suggest that the nonlinear funds do not perform well compared with the linear funds particularly during financial distress periods. Given that relative performance is an important factor in attracting funds and growing AUM (Do et al., 2014, forthcoming; Getmansky, 2012; Lajbcygier, 2008), it is of interest to investigate whether the nonlinear hedge funds, in order to remain competitive against their peers, display a higher proclivity toward altering their risk exposures.

To this end Table 7.6 presents the results pertaining to the analysis of persistence of form of funds' exposures. The cross tables contain percentages of funds classified over two five-year consecutive periods as linear exposure funds ('Linear'), nonlinear exposure funds ('Nonlinear'), funds with insignificant exposures ('None'), and failed funds ('Fail'). Fund's form of exposures during the first period is given in columns and the form of exposures in the second period is in rows. The tables are populated for seven pairs of rolling windows starting from 1994-2003 and ending in 2000-2009. The figures are expressed as proportion of the number of survived funds, while numbers in the brackets give the proportions including funds which stopped reporting in the second period (referred to as failed funds in Table 7.6)[117]. For instance, from the first table it is observed that 79% of funds classified as linear during 1994-1998 survived and retained the form of exposures during 1999-2003, whereas 35% of funds which had linear exposures during 1994-1998 failed during the next five years.

[117] It is necessary to note that a fund can drop from the database due to a number of reasons and fund's failure or liquidation is just one of them. Drop reason codes in the TASS database include: stop reporting, unable to contact, closed to new investment, merged into another fund, and dormant funds.

The table reveals several interesting findings. Firstly, nonlinear exposures seem to be less persistent than linear exposures. Only 15-25% of funds which have nonlinear exposures in first period retain nonlinear exposures in the next period, while on average 70-85% of funds classified initially as linear retain linear exposures in the next period. This result is supported by the conditional kappa coefficient which measures the level of agreement between forms of exposures in two periods. The conditional kappa is very low (<0.10) and insignificant for the nonlinear funds and much higher (around 0.2-0.3) and statistically significant for the linear funds. The conditional kappa indicates low persistence of the nonlinear form of exposures and some persistence of the linear form. Continuing the analysis, it is observed that around 55-75% of nonlinear funds alter their risk exposures and become linear funds in the next period. This finding support the notion that fund managers take action on poor relative performance and change the risk-return profile of their funds to deviate less from the linear peers.

In regards to the funds with insignificant exposures, this group demonstrates a moderate level of persistence. Around 35%-50% of funds with risk-neutral profile in one period also have insignificant exposures to systematic risk factors in the second period. The conditional kappa coefficient is around 0.3 and statistically significant in all sub-periods. Persistence in this subset is understandable given that funds with low exposure to systematic risk demonstrate superior relative performance.

Overall, the total naïve measure of persistence and the total Cohen’s kappa coefficient suggest a certain level of persistence of funds’ form of exposures. The total naïve persistence statistic, which measures the proportion of funds which remain in the same subset over two periods, is 0.62 and the total Cohen’s kappa is 0.19 and highly significant.

However, the total persistence can be attributed primarily to the strong persistence of the linear form of exposures.

Table 7.6 Persistence of Funds' Form of Systematic Risk Exposure

The table presents measures of persistence of funds' form of exposure to systematic risk from 1994 to 2009. The two-way contingency tables report percentages of funds with linear, nonlinear and no exposures ('none') to systematic risk during two subsequent five-year periods with the form of exposure in the first period given in rows and the form of exposure in the second period given in columns. The form of the exposure is determined based on the goodness of fit of the linear model SLM14 and the nonlinear model SGAML14 fitted to the residuals of the linear model. The percentages are proportions of funds with certain form of exposures. Other reported statistics are: the conditional Cohen's kappa (Cond. kappa) with associated t-statistic; the total naïve measure of persistence (Naïve) and the total Cohen's kappa (Kappa) with t-statistic. Values of the conditional and the total Cohen's kappa marked with *, **, and *** are significant at the 10, 5, and 1% levels, respectively.

	1994-1998 / 1999-2003						1995-1999 / 2000-2004					
Exposure	Linear	Nonlinear	None	Fail	Cond. Kappa	t-stat	Linear	Nonlinear	None	Fail	Cond. Kappa	t-stat
Linear	79% (52%)	9% (6%)	12% (8%)	(35%)	0.21***	3.58	80% (55%)	12% (8%)	8% (6%)	(32%)	0.29***	5.88
Nonlinear	66% (32%)	24% (12%)	11% (5%)	(51%)	0.16**	2.21	61% (35%)	22% (13%)	18% (10%)	(42%)	0.09	1.45
None	57% (32%)	4% (2%)	39% (22%)	(43%)	0.27***	4.30	44% (26%)	18% (10%)	38% (22%)	(41%)	0.28***	5.04
Total	Naïve	Kappa	t-stat				Total	Naïve	Kappa	t-stat		
Persistence	0.66	0.22***	5.54				Persistence	0.67	0.24***	7.27		
	1996-2000 / 2001-2005						1997-2001 / 2002-2006					
Exposure	Linear	Nonlinear	None	Fail	Cond. Kappa	t-stat	Linear	Nonlinear	None	Fail	Cond. Kappa	t-stat
Linear	76% (52%)	14% (9%)	11% (7%)	(31%)	0.26***	6.22	84% (56%)	9% (6%)	7% (5%)	(33%)	0.32***	6.27
Nonlinear	68% (43%)	11% (7%)	21% (13%)	(37%)	-0.03	-0.75	76% (52%)	18% (12%)	6% (4%)	(32%)	0.08	1.27
None	35% (22%)	15% (10%)	50% (32%)	(36%)	0.38***	7.27	48% (30%)	9% (6%)	42% (26%)	(38%)	0.33***	7.41
Total	Naïve	Kappa	t-stat				Total	Naïve	Kappa	t-stat		
Persistence	0.63	0.23***	7.69				Persistence	0.66	0.25***	9.09		
	1998-2002 / 2003-2007						1999-2003 / 2004-2008					
	Linear	Nonlinear	None	Fail	Cond. Kappa	t-stat	Linear	Nonlinear	None	Fail	Cond. Kappa	t-stat
Linear	84% (51%)	8% (5%)	8% (5%)	(39%)	0.24***	4.34	69% (38%)	27% (15%)	4% (2%)	(45%)	0.18***	5.77
Nonlinear	79% (50%)	11% (7%)	10% (6%)	(36%)	0.03	1.50	53% (27%)	42% (22%)	5% (3%)	(48%)	0.19***	2.58
None	59% (35%)	3% (2%)	38% (22%)	(41%)	0.28***	6.46	42% (22%)	28% (15%)	30% (16%)	(48%)	0.23***	6.49
Total	Naïve	Kappa	t-stat				Total	Naïve	Kappa	t-stat		
Persistence	0.61	0.17***	6.81				Persistence	0.58	0.2***	8.16		
	2000-2004 / 2005-2009						Overall					
	Linear	Nonlinear	None	Fail	Cond. Kappa	t-stat	Linear	Nonlinear	None	Fail	Cond. Kappa	t-stat
Linear	66% (34%)	26% (13%)	8% (4%)	(49%)	0.13***	4.44	76% (46%)	16% (10%)	8% (5%)	(39%)	0.21***	13.07
Nonlinear	61% (30%)	24% (12%)	15% (7%)	(51%)	-0.03	-0.60	68% (40%)	20% (12%)	11% (7%)	(42%)	0.04	1.35
None	38% (16%)	26% (11%)	36% (15%)	(59%)	0.26***	5.98	46% (25%)	16% (9%)	39% (21%)	(45%)	0.29***	16.26
Total	Naïve	Kappa	t-stat				Total	Naïve	Kappa	t-stat		
Persistence	0.56	0.13***	5.30				Persistence	0.62	0.19***	17.66		

7.4 Conclusion

This chapter extends the analysis of hedge funds' nonlinear risk exposures to the individual fund level. There are several main findings.

First of all, the funds are classified by the form of their risk exposures and proportions of funds with linear risk exposures, nonlinear exposures and market-neutral funds are estimated. Classification is based on the R^2 coefficient of the optimal linear and nonlinear regression models fitted to each fund. The critical values of R^2 are determined via a simulation procedure. It is found that majority of funds, roughly two-thirds, exhibit only linear exposures, while nonlinear features are present in exposures of around one-fifth of funds; the rest of the funds have very low linear and nonlinear R^2 coefficients indistinguishable statistically from zero and considered market-neutral funds.

The fact that in more than half of the funds there is no evidence of nonlinearities is interesting, because nonlinearities have been detected in many hedge fund styles at the portfolio level. It also suggests that the styles do not represent homogeneous collections of funds; rather there is a substantial variation among funds within the styles in terms of the investment approach and the risk-return profile. As a result, evaluation of nonlinearities based on hedge fund indices only can be misleading, because it ignores the differences between the funds following the same style.

The estimates of the number of linear and nonlinear funds obtained in this chapter match closely those reported by Bollen (2013) for the linear funds, and Diez de los Rios and Garcia (2011) for the nonlinear funds.

Moreover, from this study it becomes clear that out of one-third of funds identified as market-neutral in Bollen (2013), around half actually have exposures to systematic risk, but these exposures have a nonlinear form. Thus, classification of funds into three groups by form of risk exposures is more complete. It also enables to reconcile the differences between funds' classification schemes into linear and market-neutral funds employed by Bollen (2013) and linear and nonlinear funds used by Diez de los Rios and Garcia (2011). The variation of linear and nonlinear funds across styles is consistent with common expectations, as more linear funds are detected in directional styles and more nonlinear funds in arbitrage categories.

Secondly, performance analysis of the subsets of funds grouped by form of their risk exposures demonstrates that nonlinear funds on average are inferior to linear funds in terms of raw returns, risk-adjusted returns and negative tail risk. Additional investigation over three sub-periods reveals that the nonlinear funds underperformed the linear funds during 1995-1999 and 2005-2009, and outperformed the linear funds during 2000-2004. It is possible that relative performance of the nonlinear funds was affected by crisis events in 1998 (LTCM debacle) and 2007-2008 (the GFC). Since nonlinear funds carry higher exposure to left tail risk they are more prone to adverse impact of market distress events.

The finding of poor relative performance of nonlinear funds sends an important signal to potential hedge fund investors. The rationale for investing in hedge funds hinges on a critical assumption about the superior ability of professional fund managers to create and execute profitable trading strategies using the wide arsenal of financial instruments available to them. Hedge funds provide a laboratory to test this view. Since complex dynamic and derivative trading strategies used by hedge funds lead to a nonlinear risk-return relationship, poor performance of funds with nonlinearities provides evidence against the claim of skill among fund managers. This is consistent with earlier studies on derivatives use in hedge funds, which find no relationship (Chen, 2011) or even negative relationship between derivatives use and fund performance (Peltomäki, 2009). Also, consistent with Bollen (2013) funds with insignificant linear or nonlinear risk exposures tend to perform better than other funds.

Finally, when examining the persistence of the form that a fund's risk exposures take, it is observed that funds with nonlinearities more frequently alter their risk-return profile than the linear funds and the funds with insignificant exposures. More than half of the funds classified initially as nonlinear later change their strategies and become linear funds, i.e. exhibit only linear exposure to systematic risk. Given that relative performance is an important factor affecting the growth of AUM, the tendency of nonlinear funds to change their risk-return profiles in order to deviate less from their more successful linear peers appears reasonable.

Chapter 8 Results - Hedge Fund Replication and Nonlinear Risk

This chapter presents empirical results related to the third research question on the linear and nonlinear replication of hedge fund returns. The chapter aims to investigate several issues. The first area of investigation is related to the replication of nonlinear risk exposures of hedge funds documented in previous chapters. If nonlinear risk exposures are a genuine source of risk and risk premium, then nonlinear clones should produce a better replication of hedge fund style returns than linear clones. Hedge fund replication is an active area of research which is particularly relevant for investors and practitioners. An accurate replication model of aggregate hedge fund style performance would provide investors with an alternative and cost efficient way of gaining access to the hedge fund beta. So far, nonlinear replication models have not been explored in the literature. Therefore, improving the accuracy of replication models by accommodating hedge fund nonlinearities is essential.

The second area of investigation is concerned with comparison of linear and nonlinear replicators of two types of hedge fund benchmarks, i.e. non-investable broad style indices and investable hedge fund indices. So far, most of the research in the literature has focused on linear replication of non-investable hedge fund indices and concluded that overall hedge fund clones are systematically inferior to hedge funds (Amenc et al., 2010; Hasanhodzic & Lo, 2007). Given that the vast majority of funds in hedge fund databases are not investable[118] it is argued in this thesis that comparison of passive replication strategies which use liquid and

[118] Only 14% of funds in the TASS database were open as of 2010

tradable underlying instruments with non-investable indices is disputable. Hence, this chapter investigates whether conclusions in the literature are affected by the choice of non-investable benchmarks and whether they would change if clones were compared against investable indices.

Finally, the comparison of performance between non-investable and investable indices is of interest in itself, though not the main focus of this thesis. The very concept of creating an investable hedge fund index raises many questions, because of the lack of transparency, liquidity and other issues related to underlying assets (i.e. individual hedge funds) of such an index. Thus, the findings pertaining to the differences between the performance characteristics of the two types of indices contribute to the emerging literature on hedge fund indexation and are particularly interesting and relevant to practitioners.

As explained earlier (Section 4.3) the main source of data for the hedge fund replication analysis is the HFR database and specifically *HFRI* non-investable broad hedge fund style indices and *HFRX* investable indices. HFRX indices represent equal-weighted portfolios comprising a subset of open to new investment funds. These indices are constructed using a proprietary methodology developed by HFR and are designed to be representative of the performance of the hedge fund universe and hedge fund styles. In addition to replication of HFR indices, replication of TASS indices[119] which are used in the first part of this thesis is carried out and results are presented at the end of this chapter.

This chapter begins with the discussion of descriptive statistics of the two sets of HFR indices, presented in Section 8.1. Section 8.2 presents the results on tracking accuracy of HFRI and HFRX linear and nonlinear replicating portfolios. Section 8.3 investigates performance

[119] TASS indies are not investable

characteristics of HFR clones. Section 8.4 discusses the results of replication analysis of TASS indices. Section 8.5 makes the concluding comments.

8.1 Descriptive Statistics of HFR Indices

Table 8.1 presents descriptive statistics of HFRI and HFRX style indices over the period from January 1998 to February 2014. The table highlights several important differences between the two types of indices. Firstly, investable indices have lower mean return comparing with non-investable indices across all the styles. The average annualized return of an equal-weighted portfolio of all HFRX funds is 2.7% p.a. lower than the return of an equal-weighted portfolio of all HFRI funds (the returns are 4.5% and 7.2% respectively for HFRX and HFRI EW indices). Only in two styles (ED and EH) (excluding equal-weighted aggregate index) lower returns are accompanied by lower risk as measured by the standard deviation. Lower raw returns provide support to the "Groucho Marx" effect proposed in Section 3.2.3: investable funds have capacity because they do not perform well and no one is interested to invest in them. Secondly, out of nine styles five HFRX portfolios have higher exposure to negative tail risk than HFRI portfolios. It is evidenced by higher values of the kurtosis, higher negative skewness and lower minimum returns. Thirdly, all HFRI and HFRX indices exhibit non-normal pattern of returns: the Jarque-Bera test rejects the hypothesis of normality at 1% level for all the styles except for the HFRX Equity Market Neutral style for which the normality is rejected at 5% level. Finally, the correlation between the two indices across most of the styles is high, but not perfect. It varies in the range between 0.71 for the Macro style to 0.91 for the Event Driven style. The only exception is the Equity Market Neutral style for which the correlation is as low as 0.5. Equity market neutral funds are likely to have fewer common factor exposures and carry more idiosyncratic risk; therefore, it is more complicated to create a representative index of their performance with a small subset of open for new investments funds and that leads to low correlation.

Overall the results in Table 8.1 provide preliminary evidence suggesting that HFRX indices may not be fully representative of the broad hedge fund universe. As an illustration, compare the correlation between HFRI equally weighted composite index (EW) and its investable analogue HFRX EW index with the correlation between the S&P 500 index and its tracker fund SPDR S&P 500. HFRX index had correlation of just above 0.8 and on average underperformed its non-investable benchmark by 2.7% p.a., while the S&P 500 tracker fund had the correlation of more than 0.99 and underperformed the benchmark by mere 0.00075% on a pre-fee basis during 1998 to 2013[120]. Clearly the task of providing investors with a broad exposure to hedge fund alpha and/or beta is more complicated than tracking the equity market index. The analogy to stock market indices breaks down because underlying constituents of a hedge fund index are not liquid. Only 14% of funds in the TASS Live database were open to new investors as of September 2010. This fact provides motivation to explore other ways of how investors could access hedge fund alpha and/or beta without relying on investable indices. One of the ways is through synthetic replication of hedge fund indices. Accordingly, the next two sections discuss the results on tracking accuracy and performance of linear and nonlinear replicating portfolios of hedge fund style indices.

[120] Author's calculation; the data on the SPDR S&P 500 index fund are sourced from DataStream

Table 8.1 Descriptive Statistics of HFRI and HFRX Indices

The table presents descriptive statistics of HFRI and HFRX hedge fund style indices from January 1998 to February 2014: annualized mean (Mean), annualized standard deviation (SD), skewness (Skew), kurtosis, minimum (Min), maximum (Max), Jarque-Bera test statistic (JB) and correlation between the two indices. Superscripts *, ** and *** near JB statistic figures indicate the statistical significance at 10%, 5% and 1% levels, respectively. The hedge fund styles are: Convertible Arbitrage, Distressed/Restructuring, Event Driven, Equity Hedge, Equity Market Neutral, Hedge Fund Composite Equally Weighted (EW), Global Hedge Fund Composite Value Weighted (GL), Macro (M), Merger Arbitrage (MA), and Relative Value Arbitrage (RVA).

Style	Index	No. of Obs.	Mean	SD	Skew	Kurtosis	Min	Max	JB	Cor
CA	HFRI	194	0.072	0.076	-2.714	22.225	-0.16	0.097	4231.133***	0.87
	HFRX	194	0.019	0.114	-7.102	68.462	-0.347	0.067	39517.952***	
DS	HFRI	194	0.086	0.066	-1.495	5.042	-0.085	0.055	277.752***	0.78
	HFRX	194	0.035	0.071	-1.688	7.69	-0.117	0.061	570.162***	
ED	HFRI	194	0.083	0.069	-1.35	4.114	-0.089	0.051	195.708***	0.91
	HFRX	194	0.056	0.066	-1.48	4.786	-0.09	0.048	255.998***	
EH	HFRI	194	0.082	0.096	-0.197	2.06	-0.095	0.109	35.548***	0.89
	HFRX	194	0.061	0.084	-0.378	3.3	-0.1	0.098	92.642***	
EMN	HFRI	194	0.042	0.032	-0.243	2.396	-0.029	0.036	48.314***	0.50
	HFRX	194	0.01	0.039	-0.374	0.619	-0.038	0.029	7.617**	
EW	HFRI	194	0.072	0.072	-0.62	2.772	-0.087	0.076	74.545***	0.83
	HFRX	194	0.045	0.05	-2.674	14.895	-0.099	0.033	2024.638***	
GL[a]	HFRI									
	HFRX	194	0.055	0.064	-0.689	5.194	-0.093	0.059	233.383***	
M	HFRI	194	0.063	0.057	0.499	0.992	-0.037	0.068	16.009***	0.71
	HFRX	194	0.053	0.084	0.399	1.433	-0.074	0.085	21.747***	
MA	HFRI	194	0.061	0.036	-1.545	6.33	-0.057	0.031	401.016***	0.84
	HFRX	194	0.054	0.036	-1.09	3.335	-0.046	0.033	128.325***	
RVA	HFRI	194	0.075	0.045	-2.848	15.059	-0.08	0.039	2095.365***	0.90
	HFRX	194	0.042	0.07	-2.822	16.937	-0.141	0.068	2576.405***	

[a]A value-weighted global hedge fund index does not exists in HFRI set

8.2 Tracking Accuracy of HFR Replicating Portfolios

The previous section highlights some concerns related to poor relative performance of investable hedge fund indices and their far from perfect tracking efficiency. This section presents the results on tracking accuracy of synthetic linear and nonlinear replicating portfolios of HFRI and HFRX indices. Performance related measures are compared and discussed in the next section.

Following the methodology developed in Sections 5.3.1-5.3.2 for each HFRI and HFRX style index a linear and a nonlinear replicating portfolio has been constructed and evaluated out-of-sample. Table 8.2 reports the details of an out-of-sample analysis of clones' ability to replicate the returns of their benchmarks. Panel A contains mean values of the difference between the monthly returns of replicating portfolios and respective hedge fund style indices with associated p-values of the two-sided heteroscedastic t-test.

The first series of result in column ΔR for HFRX-HFRI pair confirm the finding of the previous section that HFRX indices underperform HFRI indices in most of the styles in terms of raw returns; the difference between the returns is negative in all but one style (MA) and highly statistically significant (except for EMN style). On a monthly basis investable indices earn from 26 to 87b.p. less return comparing with non-investable counterparts.

Furthermore, the returns of linear and nonlinear replicating portfolios are indistinguishable statistically from the returns of respective HFRI benchmarks. The difference in raw returns is mostly negative across the styles but not significant. In other words, both types of clones generate similar returns to the original hedge fund indices in all the styles. This provides a strong argument in favour of hedge fund replication as there is no evidence that clones are systematically inferior to hedge funds. It also suggests that aggregate hedge fund performance is driven mostly by alternative beta, i.e. systematic risk exposures to various factors, rather than alpha.

In addition, the absolute value of the raw returns' difference is lower for nonlinear clones than for linear clones in six out of nine styles and slightly higher only in one style. This result indicates that nonlinearities are important and taking them into account may help to further improve the accuracy of the replication.

The results for HFRX clones differ. The most striking difference is that while HFRI clones slightly underperform their benchmarks by up to -25b.p. per month (though the result is not significant as discussed), HFRX clones outperform the benchmarks in all except two cases by 10-100b.p. monthly. Higher performance is significant in five styles at 1 to 5% level rejecting the hypothesis of equal mean returns in these styles. On the one hand, higher performance is good for investors. On the other, the primary goal of an investor of a replicating fund is not the absolute performance, but low tracking error. From this perceptive HFRX clones are inferior to HFRI clones. One of the reasons of high tracking error is due to a higher idiosyncratic risk of HFRX portfolios. HFRX portfolios consist of a small subset of liquid funds (not more than ten to twenty funds)[121], whereas HFRI indices include all the funds in the styles (more than several hundreds of funds in each style)[122] ; therefore, it is expected that HFRI indices have a larger systematic risk component and HFRX indices have a larger idiosyncratic risk component, which is not replicated in clones and leads to a higher tracking error of HFRX replicators.

Panel B validates the findings as it provides median values of monthly return differences between the indices and clones. It also reports results of the nonparametric Wilcoxon signed-rank test. Apart from a bit weaker statistical significance of the differences between HFRI and HFRX style returns, these results are very similar to those presented in Panel A and all main conclusions hold as well.

[121] For instance, the total number of funds in aggregate HFRX Global Hedge Fund Index is around 60 (see HFR web-site); thus, individual strategy indices are unlikely to have more than 10-20 of underlying constituents. HFR does not publicly disclose the total number of funds in HFRX indices.

[122] The total number of funds in the HFR database is more than 7,500; see Section 4.3

Table 8.2 Difference in Returns of HFRI and HFRX Indices and Replicating Portfolios

The table shows the mean (median) difference in monthly returns, ΔR, of HFRX and HFRI indices (HFRX-HFRI), HFRI linear clones and HFRI indices, HFRI nonlinear clones and HFRI indices, HFRX linear clones and HFRX indices, HFRX nonlinear clones and HFRX indices as well as p-values of the associated two-sided heteroscedastic t-test (Wilcoxon signed-rank test) over the entire out-of-sample period January 2008 – February 2014. The clones are constructed using a rolling window procedure employing the linear model SLM14 and the nonlinear model SGAML14. Values of ΔR marked with *, **, and *** are significant at the 10, 5, and 1% levels, respectively.

Panel A: Two-Sided Heteroscedastic t-Test

	HFRX-HFRI		HFRI Linear Clone - HFRI		HFRI Nonlinear Clone - HFRI		HFRX Linear Clone - HFRX		HFRX Nonlinear Clone - HFRX	
Style	ΔR	**p-value**	ΔR	**p-value**	ΔR	**p-value**	ΔR	**p-value**	ΔR	**p-value**
CA	-0.007**	0.030	0.0003	0.900	-0.0003	0.904	0.0097**	0.037	0.0088**	0.047
DS	-0.0087***	0.000	0.0003	0.843	0.0000	0.986	0.0094***	0.000	0.0094***	0.000
ED	-0.0026***	0.008	-0.0002	0.868	-0.0003	0.796	0.0010	0.458	0.0012	0.353
EH	-0.0037***	0.007	-0.0003	0.782	-0.0002	0.844	0.0038**	0.028	0.0044**	0.016
EMN	-0.0020	0.106	-0.0007	0.494	-0.0003	0.789	0.0012	0.410	0.0015	0.319
EW	-0.0032***	0.005	-0.0004	0.642	-0.0004	0.675	0.0033***	0.006	0.0033***	0.003
M	-0.0035**	0.038	-0.0025	0.235	-0.0024	0.223	-0.0017	0.502	-0.0008	0.750
MA	0.0000	0.994	-0.0014	0.107	-0.0012	0.117	-0.0005	0.611	-0.0001	0.897
RVA	-0.0047***	0.003	-0.0012	0.252	-0.0006	0.499	0.0054***	0.008	0.0055***	0.008

Panel B: Wilcoxon Signed-Rank Test

	HFRX-HFRI		HFRI Linear Clone - HFRI		HFRI Nonlinear Clone - HFRI		HFRX Linear Clone - HFRX		HFRX Nonlinear Clone - HFRX	
Style	ΔR	**p-value**	ΔR	**p-value**	ΔR	**p-value**	ΔR	**p-value**	ΔR	**p-value**
CA	-0.0013*	0.089	0.0007	0.979	-0.0004	0.451	0.0067*	0.071	0.0054*	0.079
DS	-0.0064***	0.000	-0.0003	0.706	-0.0004	0.734	0.006***	0.000	0.0065***	0.000
ED	-0.0021**	0.013	-0.0007	0.360	-0.0006	0.284	0.0006	0.332	0.0010	0.269
EH	-0.003**	0.014	-0.0002	0.931	-0.0004	0.910	0.0029**	0.033	0.0027**	0.016
EMN	-0.0024**	0.015	-0.0012	0.166	-0.0006	0.447	0.0005	0.590	0.0012	0.451
EW	-0.0029**	0.010	-0.0006	0.821	-0.0002	0.893	0.0027***	0.007	0.0022***	0.002
M	-0.0031**	0.029	-0.0005	0.477	-0.0018	0.410	-0.0016	0.927	-0.0016	0.880
MA	-0.0001	0.923	-0.0009*	0.087	-0.0011**	0.039	-0.0003	0.829	-0.0008	0.914
RVA	-0.0028***	0.000	-0.0014*	0.057	-0.0015**	0.045	0.0036***	0.007	0.0029***	0.003

To examine differences between linear and nonlinear replicating approaches at greater depth Table 8.3 presents the results of the analysis using four other measures of tracking efficiency: the annualized tracking error (TE), the mean absolute error (MAE), the absolute excess return (AER) and the cumulative excess return (CER). Additionally, Figure 8.1 compliments the numerical analysis with time-series graphs of returns of HFRI and HFRX indices and their clones, while Figure 8.2 presents cumulative performance charts.

As can be seen from Panel A overall over the whole out-of-sample period from January 2008 to February 2014 HFRI nonlinear replicating portfolios have lower tracking error and mean absolute error than linear HFRI clones and much lower tracking error and MAE compared with HFRX indices, which are supposed to be representative of HFRI style benchmarks. On average the tracking error of nonlinear clones is 14b.p. less the tracking error of linear clones and 86b.p. p.a. less the tracking error of HFRX indices. It suggests that genuine nonlinearities exist in hedge fund indices which are statistically and economically significant.

Although nonlinear clones on average have lower tracking error, their tracking efficiency varies across the styles. For example, tracking errors of linear and nonlinear clones in the Equity Market Neutral category and the Equal Weighted Composite Hedge Fund category match closely. In other styles such as the Macro, the Relative Value Arbitrage, the Merger Arbitrage and the Event Driven the difference is larger: 38, 34, 32 and 28b.p. p.a. respectively. Lower tracking error of nonlinear clones in HFR arbitrage styles provides additional evidence of the importance of nonlinearities in arbitrage related hedge fund strategies identified earlier for TASS indices (see Section 6.2). Nonlinear clones of the Merger Arbitrage and the Relative Value Arbitrage HFRI style indices also exhibit the lowest tracking error of 2.34% and 2.72% among all clones, suggesting that the SGAML14 model achieves some success in explaining returns of these styles. Nonlinearities in strategies involving risk arbitrage techniques have been documented in the literature before (Agarwal & Naik, 2004; Giannikis & Vrontos, 2011; Mitchell & Pulvino, 2001).

Considering time-series graphs presented in Figure 8.1 it can be seen that both types of HFRI replicating portfolios (linear and nonlinear) exhibit good tracking ability in many styles and particularly in the Equally Weighted Composite, the Convertible Arbitrage, the Distressed Restructuring, the Event Driven, the Equity Hedge, the Merger Arbitrage and the Relative Value categories. In contrast, replication of returns in the Equity Market Neutral and the Macro styles with factor approach even after accounting for nonlinearities seems problematic. Equity Market Neutral funds clearly have less common factor exposures than other categories of hedge funds, even though they are not completely market-neutral (Patton, 2009). Macro funds, perhaps, are too heterogeneous category for their replicate with a single model. There has not been any study focusing exclusively on Macro funds yet.

As far as clones of HFRX indices are concerned, the results are very similar to those for HFRI clones. In aggregate nonlinear clones have lower tracking error and mean absolute error than linear clones. However, tracking errors and MAEs of HFRX index clones are overall substantially higher when compared with HFRI clones. The average tracking error of HFRI clones is below 4%, while the average tracking error of HFRX clones exceeds 6%. One of the reasons for that due to the higher systematic risk in HFRI indices has been explained before.

Further analysis of other excess return measures, i.e. the average excess return (AER) and the cumulative excess return (CER), indicates that nonlinear HFRI clones are not only superior to linear clones and HFRX indices in terms of the tracking accuracy but in terms of the relative performance as well. On average across all the categories HFRX indices earn 4.69% p.a. lower return than HFRI benchmarks, while underperformance of linear and nonlinear HFRI replicating strategies is less dramatic and does not exceed 0.90% and 0.84%

p.a. respectively. The difference in performance of HFRI clones and HFRX indices is even more evident from the figures of cumulative excess return over six years. Since 2008 HFRX styles combined delivered negative 24.59% return relatively to HFRI benchmarks they purport to track, whereas the average cumulative excess return of nonlinear HFRI clones was negative 4.97%. On the other hand, linear and nonlinear clones of HFRX indices in contrast to HFRI clones in aggregate had positive relative performance of 4.16% and 4.37% p.a. accordingly, and that accumulated to positive 32.83% and 33.67% respectively relative to the indices.

The first two graphs in Figure 8.2 provide a clear illustration of this striking result. The first graph compares the cumulative performance of equally weighted portfolio of all HFR funds (HFRI Fund Weighted Composite Index), with the cumulative performance of eligible investable funds comprising HFRX indices and linear and nonlinear clones of both types of indices. It reveals that starting from 2009 when global markets have started to recover after the financial crisis the HFRX portfolio of funds systematically underperformed the HFRI portfolio, while HFRI clones provided a reasonably good proxy of HFRI performance. The second graph in Figure 8.2 plots similar data for a value-weighted portfolio of HFRX funds and their clones. Unfortunately, a value-weighted HFRI composite index does not exist. The graph shows that cumulative performance of HFRX clones did not drop as low as HFRX performance did during the GFC period; after the crisis HFRX funds continued underperforming synthetic clones consistently. Other strategies show similar pattern: comparing with HFRX graphs, the cumulative performance of the clones is much closer to HFRI performance.

To validate that findings about superior tracking efficiency of nonlinear clones are not a phenomenon specific to the time period analysed, a subsample analysis has been conducted.

The sample was split into two sub-periods with a single breakpoint in June 2009. This breakpoint was selected for several reasons. Firstly, it corresponds to the end of contraction phase of the latest business cycle as determined by the US National Bureau of Economic Research (NBER)[123]. Secondly, it is very close to the structural break in April 2009 identified by Edelman, Fung, Hsieh and Naik (2012).

The analysis of the tracking efficiency over two sub-periods is reported in Panel B and Panel C in Table 8.3. The results confirm that the nonlinear replication approach has consistently lower tracking error than the linear replication approach in most of the styles in both sub-periods. Nonlinear HFRI clones have lower tracking error and MAE in eight categories during the crisis period and in six categories after the crisis, while nonlinear HFRX clones have lower tracking error and MAE in six categories during the GFC period and in four categories in post-GFC period. Another interesting observation arising from comparison of two sub-periods is related to overall differences in tracking accuracy. The tracking error and the MAE of HFRX indices relatively to HFRI and all linear and nonlinear clones after the GFC is almost two-third less the figures during the crisis period.

Summarizing the findings, Table 8.3 provides evidence that synthetic replicating portfolios track monthly return time series of hedge fund style benchmarks better than investable hedge fund indices do. Furthermore, nonlinear clones have slightly lower tracking error that linear clones and the difference is more pronounced in arbitrage related styles. This confirms the evidence of nonlinearities in hedge funds and superior performance of the nonlinear approach to modeling hedge fund returns. The next section examines in detail risk-adjusted performance measures of the clones relatively to their benchmarks.

[123] http://www.nber.org/cycles/cyclesmain.html

Table 8.3 Tracking Accuracy of HFRI and HFRX Replicating Portfolios

The table presents out-of-sample annualized tracking error, mean absolute error (MAE), annualized geometric average excess return (AER) and cumulative excess return (CER) for HFRI hedge fund style benchmarks (*HFRI*), HFRX investable indices (*HFRX*) and their linear (*Lin.Clone HFRI* and *Lin.Clone HFRX*) and nonlinear (*Nonlin.Clone HFRI* and *Nonlin.Clone HFRX*) clones constructed using 14-factor models SLM14 and SGAML14 through the rolling window procedure over the periods from January 2008 to February 2014 (Panel A) and two sub-periods January 2008-June 2009 (Panel B) and June 2009-February 2014 (Panel C).

Panel A: Overall – January 2008 - February 2014

	Tracking Error					MAE					AER					CER				
Style	HFRX - HFRI	HFRI Lin.Clone - HFRI	HFRI Nonlin. Clone - HFRI	HFRX Lin.Clone - HFRX	HFRX Nonlin. Clone - HFRX	HFRX - HFRI	HFRI Lin.Clone - HFRI	HFRI Nonlin. Clone - HFRI	HFRX Lin.Clone - HFRX	HFRX Nonlin. Clone - HFRX	HFRX - HFRI	HFRI Lin.Clone - HFRI	HFRI Nonlin. Clone - HFRI	HFRX Lin.Clone - HFRX	HFRX Nonlin. Clone - HFRX	HFRX - HFRI	HFRI Lin.Clone - HFRI	HFRI Nonlin. Clone - HFRI	HFRX Lin.Clone - HFRX	HFRX Nonlin. Clone - HFRX
CA	0.0967	0.0629	0.0658	0.1398	0.1322	0.0128	0.0113	0.0110	0.0227	0.0188	-0.0853	0.0013	-0.0053	0.1141	0.1023	-0.4229	0.0078	-0.0324	0.9472	0.8230
DS	0.0624	0.0484	0.0472	0.0813	0.0763	0.0124	0.0096	0.0093	0.0146	0.0144	-0.1007	0.0027	-0.0014	0.1159	0.1159	-0.4805	0.0170	-0.0088	0.9667	0.9668
ED	0.0298	0.0370	0.0342	0.0401	0.0386	0.0067	0.0071	0.0066	0.0078	0.0079	-0.0312	-0.0032	-0.0042	0.0113	0.0139	-0.1773	-0.0195	-0.0254	0.0721	0.0888
EH	0.0419	0.0298	0.0294	0.0523	0.0547	0.0091	0.0065	0.0063	0.0112	0.0117	-0.0448	-0.0038	-0.0028	0.0457	0.0526	-0.2463	-0.0232	-0.0171	0.3169	0.3722
EMN	0.0366	0.0287	0.0285	0.0430	0.0433	0.0081	0.0056	0.0057	0.0092	0.0095	-0.0242	-0.0084	-0.0035	0.0135	0.0167	-0.1404	-0.0504	-0.0214	0.0865	0.1075
EW	0.0339	0.0282	0.0282	0.0361	0.0336	0.0074	0.0060	0.0060	0.0071	0.0066	-0.0378	-0.0057	-0.0052	0.0392	0.0394	-0.2117	-0.0347	-0.0316	0.2672	0.2695
M	0.0509	0.0632	0.0593	0.0769	0.0724	0.0106	0.0135	0.0129	0.0156	0.0151	-0.0428	-0.0319	-0.0306	-0.0237	-0.0119	-0.2364	-0.1813	-0.1742	-0.1374	-0.0714
MA	0.0212	0.0266	0.0234	0.0311	0.0301	0.0044	0.0051	0.0047	0.0060	0.0060	-0.0002	-0.0175	-0.0150	-0.0069	-0.0020	-0.0010	-0.1029	-0.0888	-0.0416	-0.0124
RVA	0.0473	0.0306	0.0272	0.0614	0.0632	0.0085	0.0060	0.0053	0.0116	0.0113	-0.0555	-0.0146	-0.0078	0.0653	0.0664	-0.2966	-0.0865	-0.0472	0.4771	0.4866
Avg.	0.0467	0.0395	0.0381	0.0624	0.0605	0.0089	0.0079	0.0075	0.0118	0.0112	-0.0469	-0.0090	-0.0084	0.0416	0.0437	-0.2459	-0.0526	-0.0497	0.3283	0.3367

Panel B: Crisis Period – January 2008 – June 2009

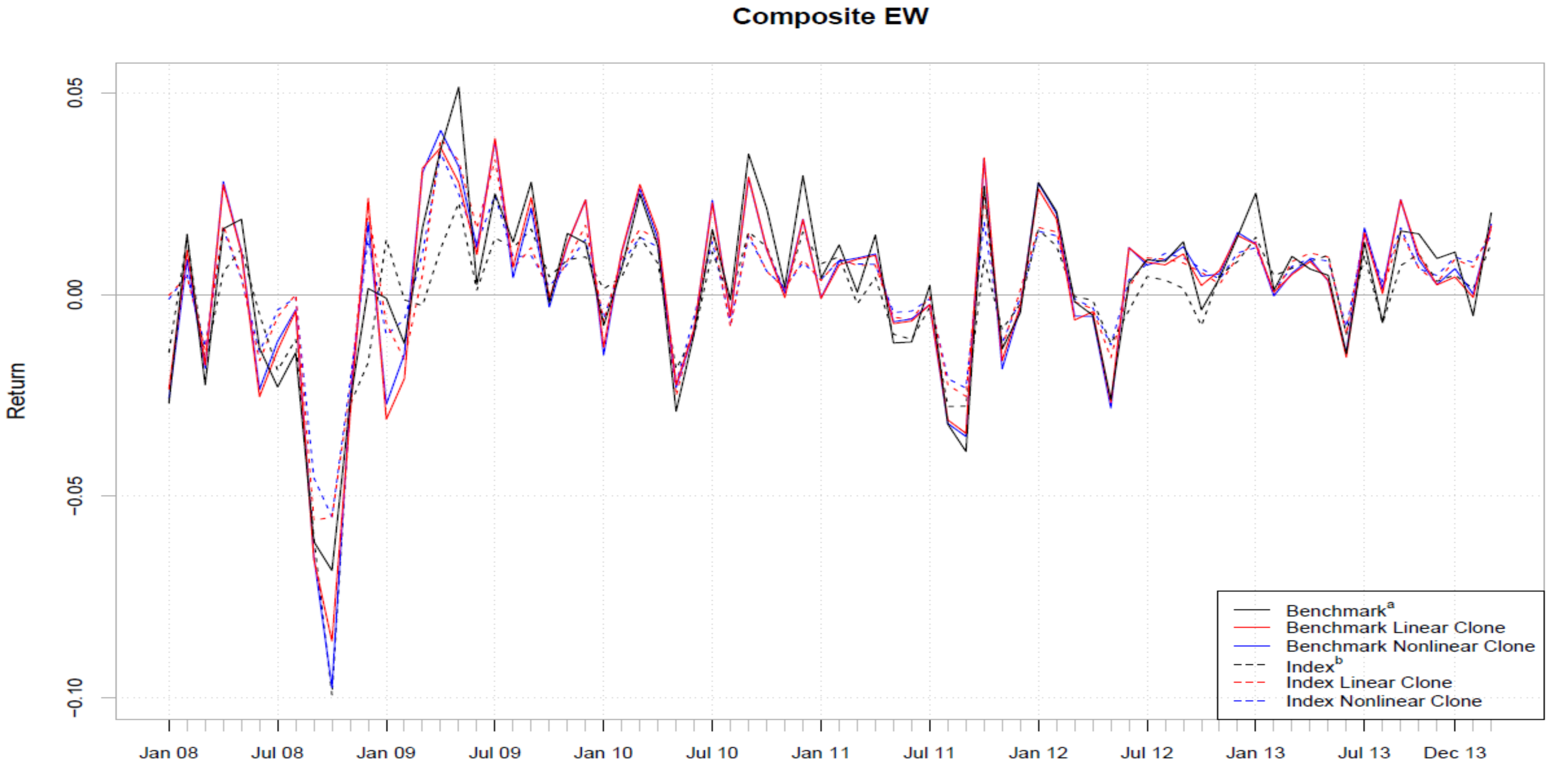
	Tracking Error					MAE					AER					CER				
Style	HFRX - HFRI	HFRI Lin.Clone - HFRI	HFRI Nonlin. Clone - HFRI	HFRX Lin.Clone - HFRX	HFRX Nonlin. Clone - HFRX	HFRX - HFRI	HFRI Lin.Clone - HFRI	HFRI Nonlin. Clone - HFRI	HFRX Lin.Clone - HFRX	HFRX Nonlin. Clone - HFRX	HFRX - HFRI	HFRI Lin.Clone - HFRI	HFRI Nonlin. Clone - HFRI	HFRX Lin.Clone - HFRX	HFRX Nonlin. Clone - HFRX	HFRX - HFRI	HFRI Lin.Clone - HFRI	HFRI Nonlin. Clone - HFRI	HFRX Lin.Clone - HFRX	HFRX Nonlin. Clone - HFRX
CA	0.1879	0.1136	0.1197	0.2607	0.2542	0.0311	0.0238	0.0231	0.0477	0.0416	-0.2916	0.0791	0.0866	0.5517	0.4410	-0.4038	0.1209	0.1326	0.9330	0.7298
DS	0.0971	0.0806	0.0783	0.1391	0.1295	0.0206	0.0168	0.0174	0.0273	0.0260	-0.1614	0.1040	0.0883	0.3342	0.3102	-0.2321	0.1599	0.1353	0.5410	0.4997
ED	0.0368	0.0631	0.0580	0.0675	0.0631	0.0089	0.0139	0.0130	0.0149	0.0147	-0.0089	0.0299	0.0300	0.0201	0.0211	-0.0133	0.0452	0.0453	0.0304	0.0318
EH	0.0460	0.0467	0.0451	0.0699	0.0766	0.0099	0.0110	0.0104	0.0169	0.0188	-0.0289	-0.0184	-0.0096	0.0407	0.0679	-0.0431	-0.0274	-0.0143	0.0617	0.1035
EMN	0.0422	0.0471	0.0473	0.0546	0.0556	0.0098	0.0105	0.0110	0.0123	0.0129	0.0071	-0.0001	0.0081	0.0177	0.0258	0.0107	-0.0002	0.0122	0.0267	0.0390
EW	0.0509	0.0463	0.0455	0.0639	0.0602	0.0113	0.0109	0.0105	0.0148	0.0140	-0.0549	-0.0195	-0.0159	0.0956	0.0989	-0.0812	-0.0291	-0.0237	0.1468	0.1520
M	0.0810	0.1038	0.0947	0.1370	0.1260	0.0195	0.0227	0.0213	0.0319	0.0298	-0.0429	-0.1188	-0.0970	-0.1149	-0.0732	-0.0636	-0.1727	-0.1419	-0.1674	-0.1078
MA	0.0328	0.0459	0.0396	0.0519	0.0495	0.0079	0.0100	0.0093	0.0108	0.0106	0.0464	-0.0542	-0.0351	-0.0773	-0.0492	0.0704	-0.0802	-0.0521	-0.1137	-0.0729
RVA	0.0861	0.0519	0.0458	0.1053	0.1106	0.0190	0.0115	0.0100	0.0226	0.0224	-0.1424	0.0204	0.0480	0.2206	0.2241	-0.2058	0.0308	0.0729	0.3486	0.3544
Avg.	0.0734	0.0665	0.0638	0.1055	0.1028	0.0153	0.0146	0.0140	0.0221	0.0212	-0.0753	0.0025	0.0115	0.1209	0.1185	-0.1069	0.0052	0.0185	0.2008	0.1922

Panel C: Post-Crisis Period – July 2009 – February 2014

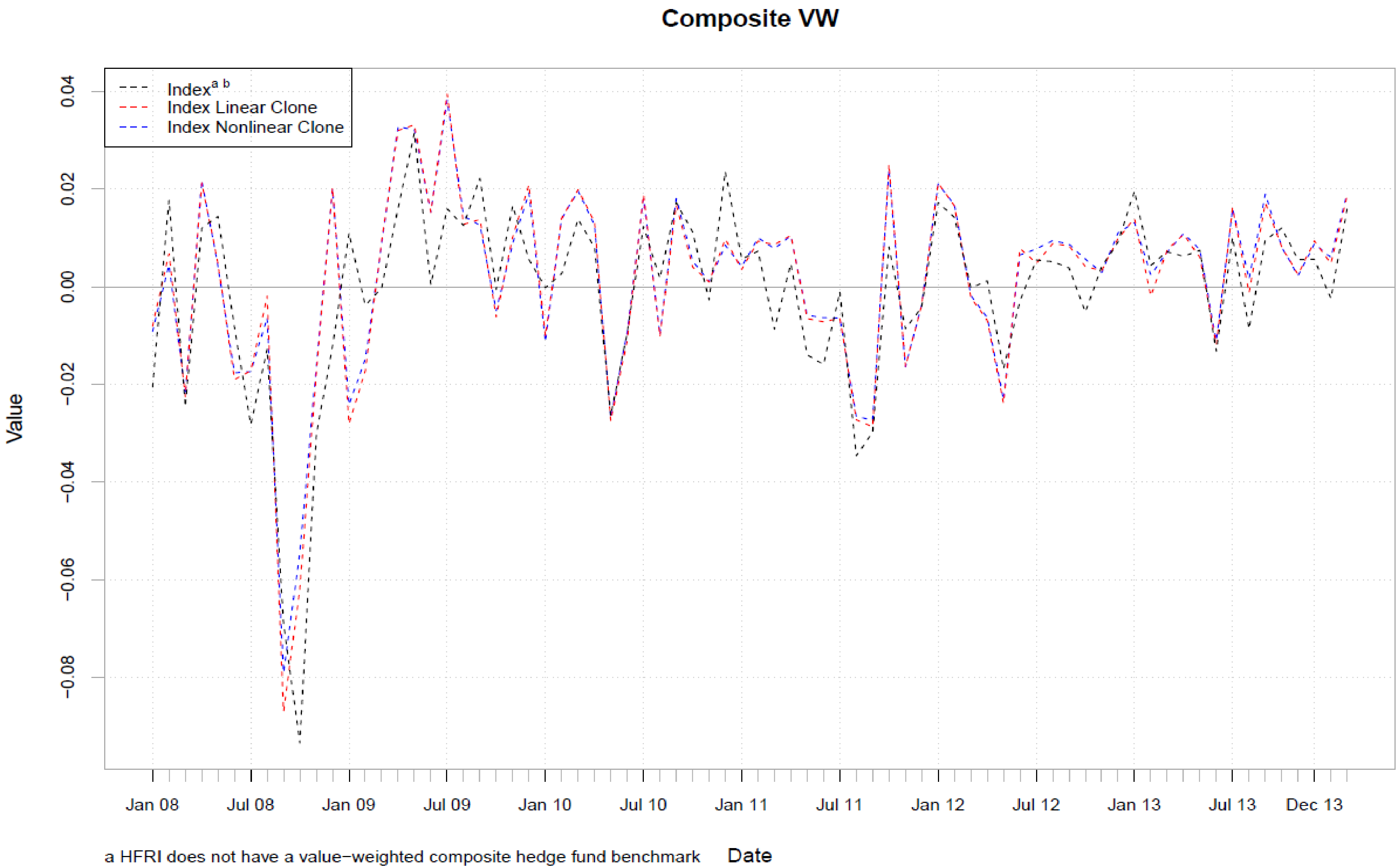
	Tracking Error					MAE					AER					CER				
Style	HFRX - HFRI	HFRI Lin.Clone - HFRI	HFRI Nonlin. Clone - HFRI	HFRX Lin.Clone - HFRX	HFRX Nonlin. Clone - HFRX	HFRX - HFRI	HFRI Lin.Clone - HFRI	HFRI Nonlin. Clone - HFRI	HFRX Lin.Clone - HFRX	HFRX Nonlin. Clone - HFRX	HFRX - HFRI	HFRI Lin.Clone - HFRI	HFRI Nonlin. Clone - HFRI	HFRX Lin.Clone - HFRX	HFRX Nonlin. Clone - HFRX	HFRX - HFRI	HFRI Lin.Clone - HFRI	HFRI Nonlin. Clone - HFRI	HFRX Lin.Clone - HFRX	HFRX Nonlin. Clone - HFRX
CA	0.0317	0.0329	0.0333	0.0630	0.0483	0.0070	0.0072	0.0071	0.0147	0.0114	-0.0070	-0.0225	-0.0332	0.0016	0.0113	-0.0321	-0.1009	-0.1457	0.0073	0.0539
DS	0.0460	0.0317	0.0311	0.0500	0.0479	0.0097	0.0072	0.0067	0.0105	0.0107	-0.0803	-0.0278	-0.0287	0.0537	0.0598	-0.3234	-0.1232	-0.1270	0.2762	0.3114
ED	0.0272	0.0230	0.0215	0.0257	0.0262	0.0060	0.0050	0.0045	0.0056	0.0057	-0.0382	-0.0136	-0.0149	0.0085	0.0116	-0.1662	-0.0618	-0.0677	0.0405	0.0553
EH	0.0405	0.0218	0.0221	0.0452	0.0455	0.0088	0.0051	0.0050	0.0093	0.0094	-0.0499	0.0009	-0.0006	0.0472	0.0478	-0.2124	0.0043	-0.0028	0.2404	0.2435
EMN	0.0346	0.0194	0.0189	0.0385	0.0385	0.0075	0.0040	0.0040	0.0082	0.0084	-0.0341	-0.0110	-0.0072	0.0122	0.0138	-0.1495	-0.0502	-0.0333	0.0582	0.0660
EW	0.0262	0.0190	0.0196	0.0203	0.0181	0.0062	0.0045	0.0045	0.0046	0.0042	-0.0323	-0.0012	-0.0017	0.0216	0.0210	-0.1420	-0.0058	-0.0081	0.1051	0.1020
M	0.0363	0.0425	0.0421	0.0421	0.0427	0.0077	0.0105	0.0101	0.0103	0.0103	-0.0428	-0.0022	-0.0082	0.0076	0.0086	-0.1846	-0.0103	-0.0377	0.0359	0.0408
MA	0.0157	0.0160	0.0148	0.0202	0.0202	0.0033	0.0035	0.0032	0.0045	0.0045	-0.0147	-0.0054	-0.0084	0.0169	0.0136	-0.0666	-0.0248	-0.0386	0.0813	0.0652
RVA	0.0238	0.0193	0.0174	0.0377	0.0367	0.0051	0.0043	0.0038	0.0081	0.0078	-0.0257	-0.0256	-0.0251	0.0197	0.0202	-0.1144	-0.1138	-0.1119	0.0953	0.0976
Avg.	0.0313	0.0251	0.0245	0.0381	0.0360	0.0068	0.0057	0.0054	0.0084	0.0080	-0.0361	-0.0120	-0.0142	0.0210	0.0231	-0.1546	-0.0541	-0.0636	0.1045	0.1151

Figure 8.1 Time Series Return of HFRI Benchmarks, HFRX Indices and Replicating Portfolios

The graphs shows returns of HFRI hedge fund style benchmarks, HFRX investable indices and their out-of-sample linear and nonlinear clones during the period from January 2008 to February 2014. Clones are constructed based on the 14-factor models SLM14 and the SGAML14 using a rolling window procedure.

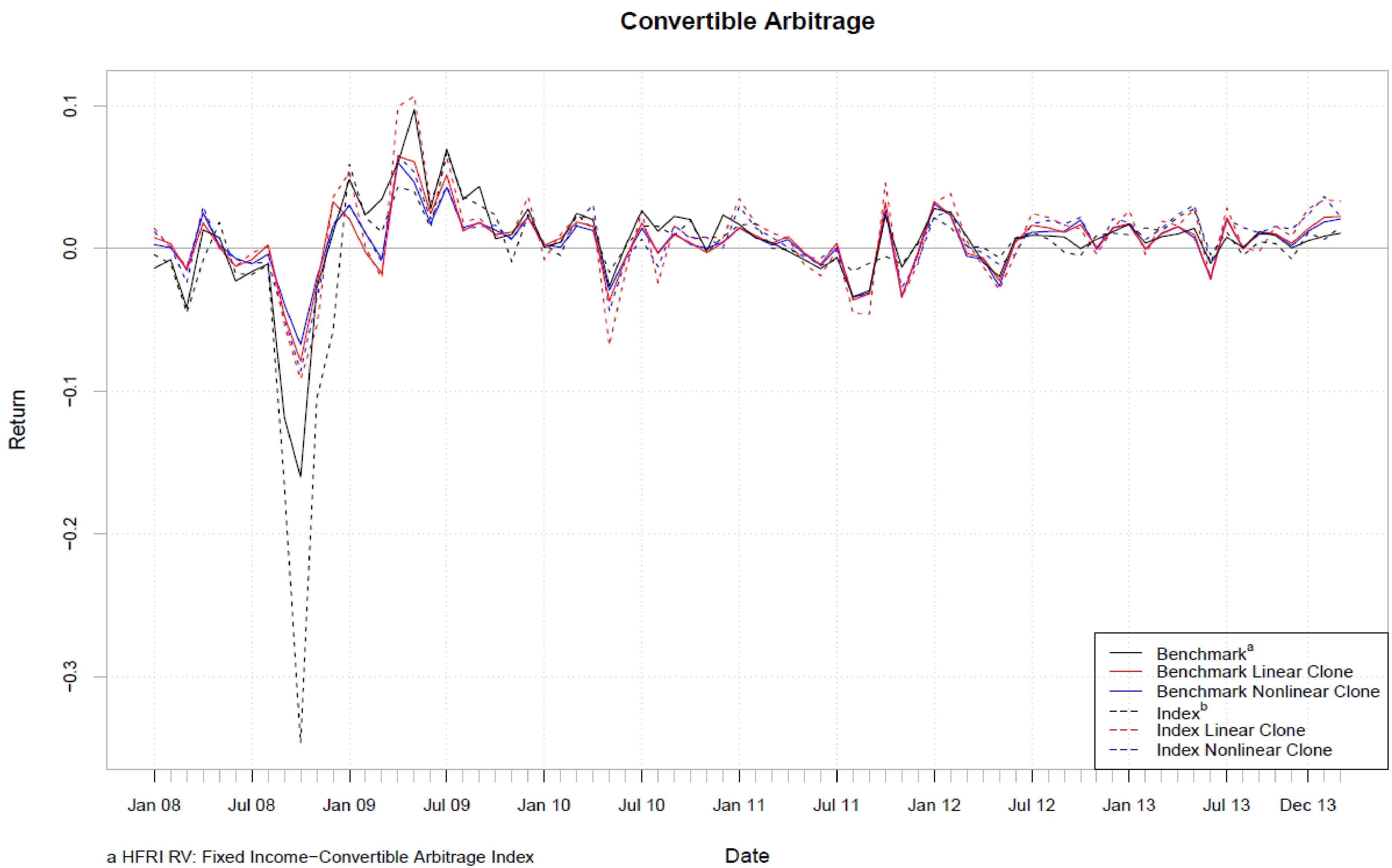


a HFRI Fund Weighted Composite Index
b HFRX Equal Weighted Strategies Index

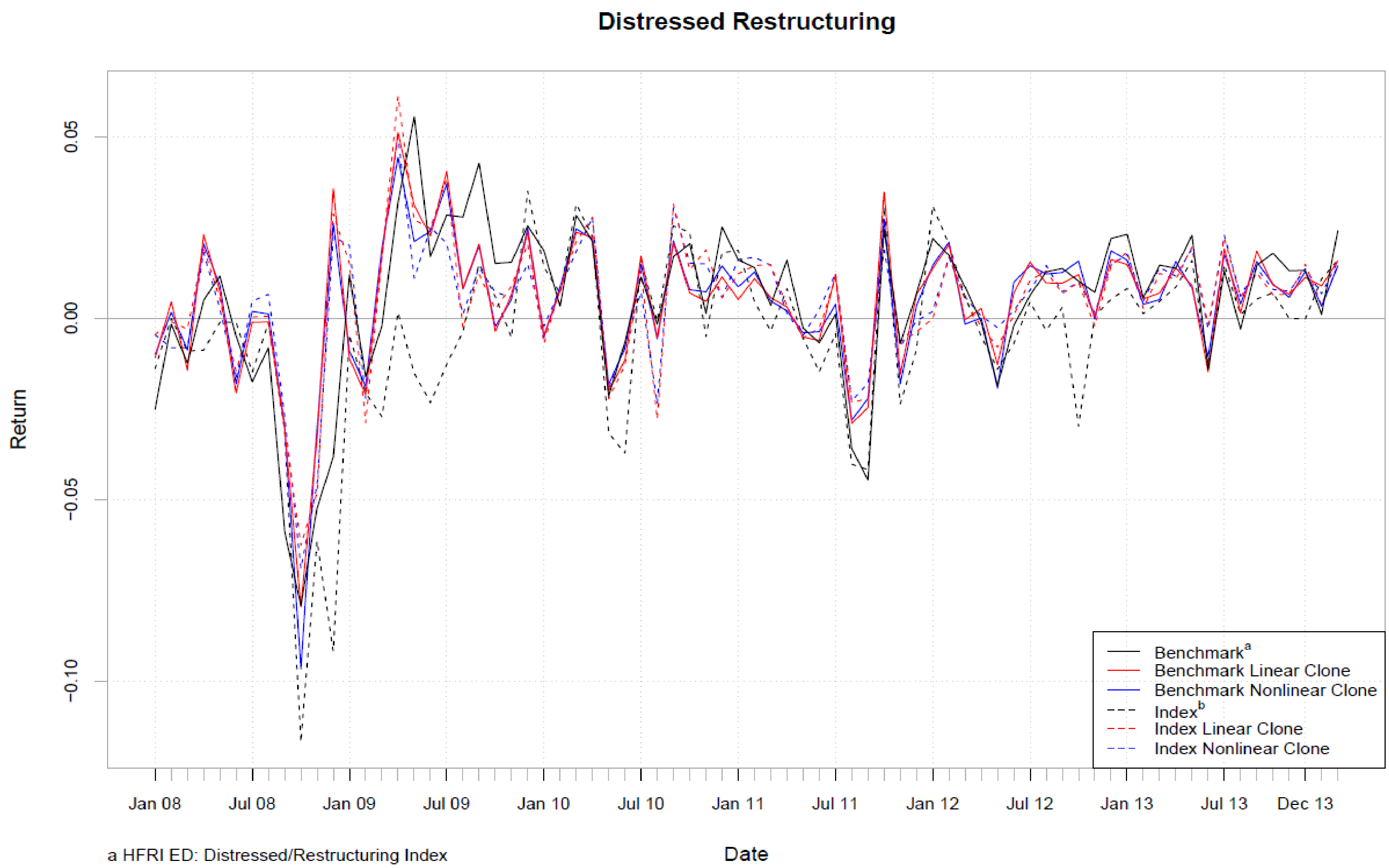


a HFRI does not have a value−weighted composite hedge fund benchmark

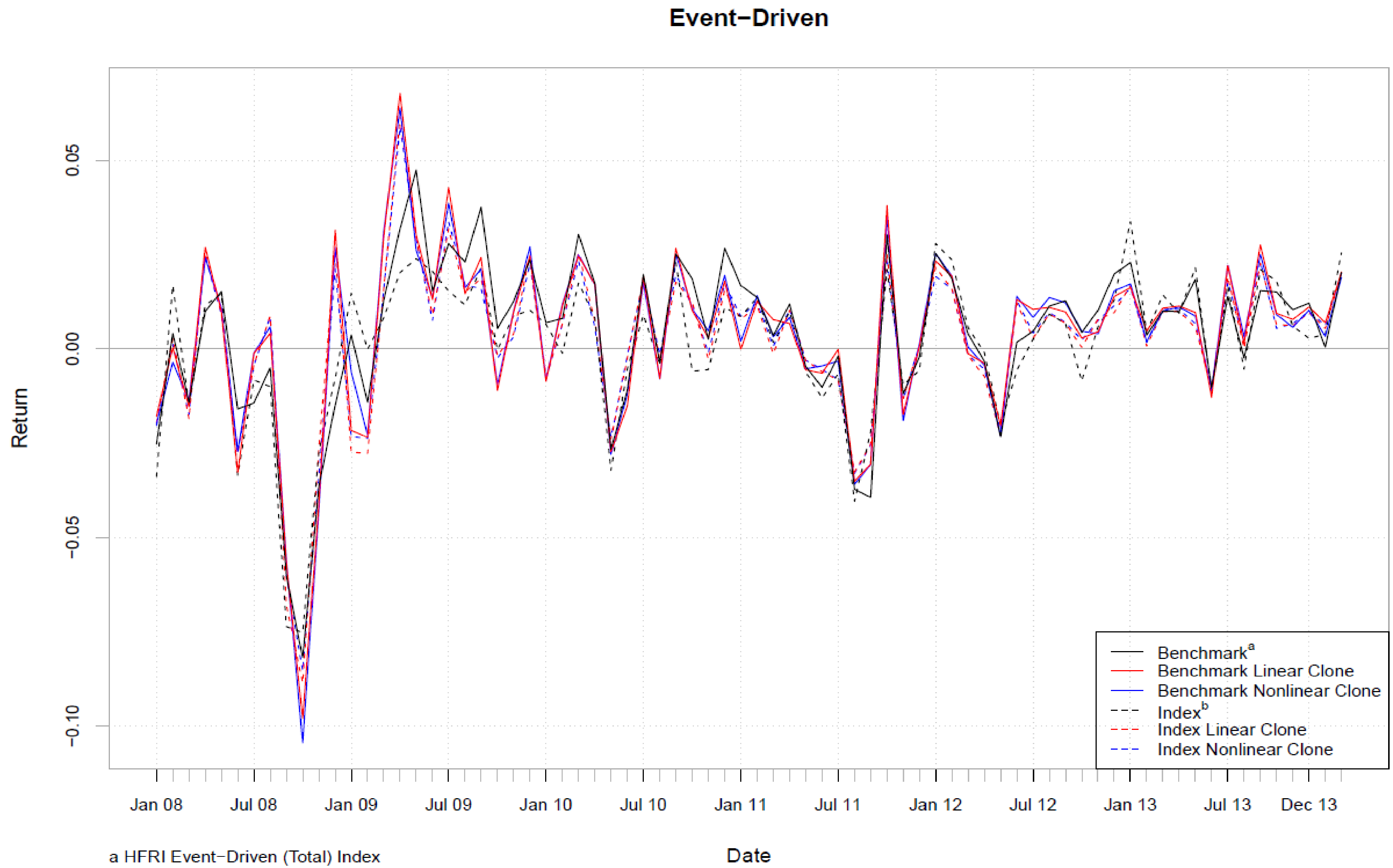
b HFRX Global Hedge Fund Index



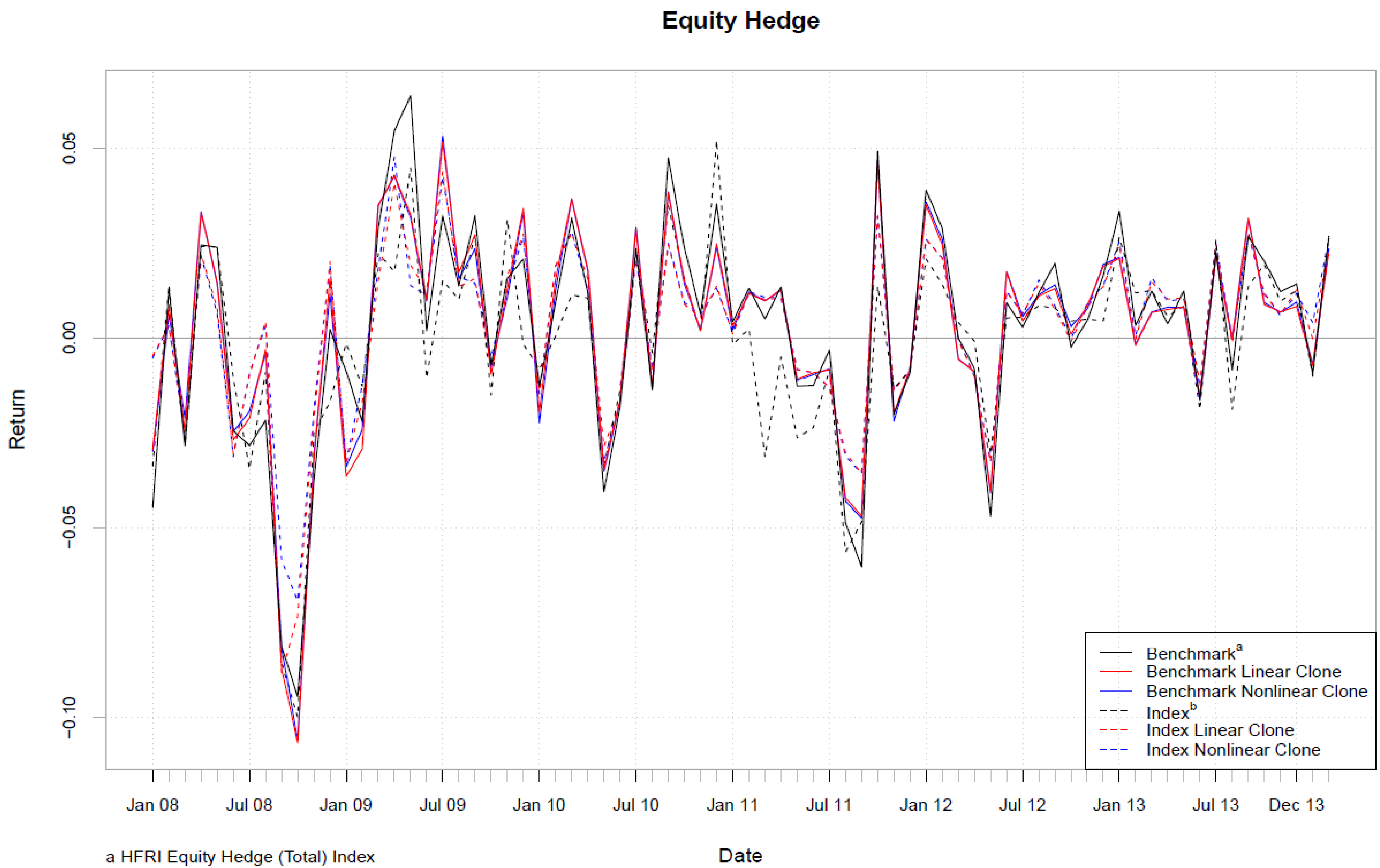
a HFRI RV: Fixed Income−Convertible Arbitrage Index
b HFRX RV: FI−Convertible Arbitrage Index



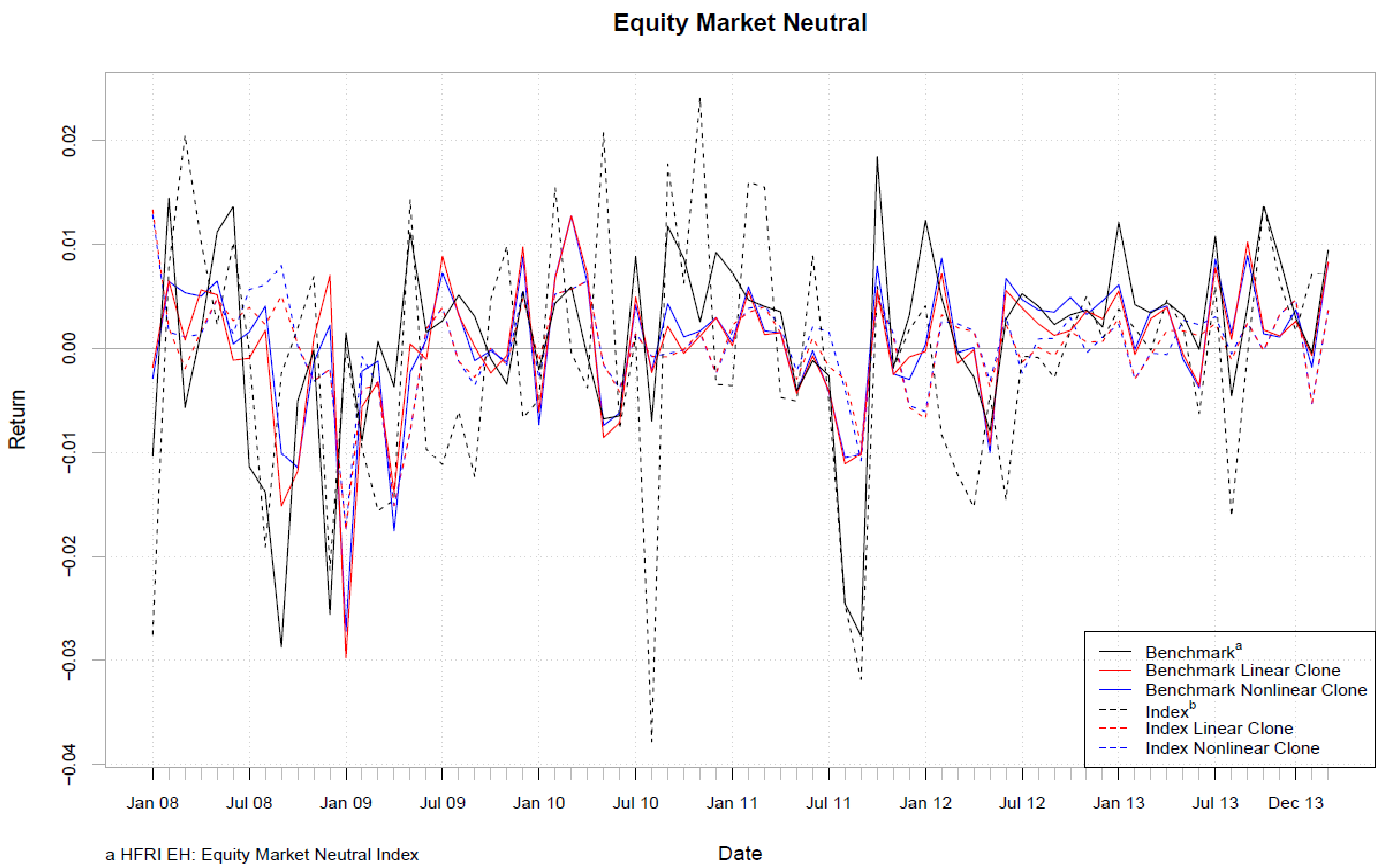
a HFRI ED: Distressed/Restructuring Index
b HFRX ED: Distressed Restructuring Index



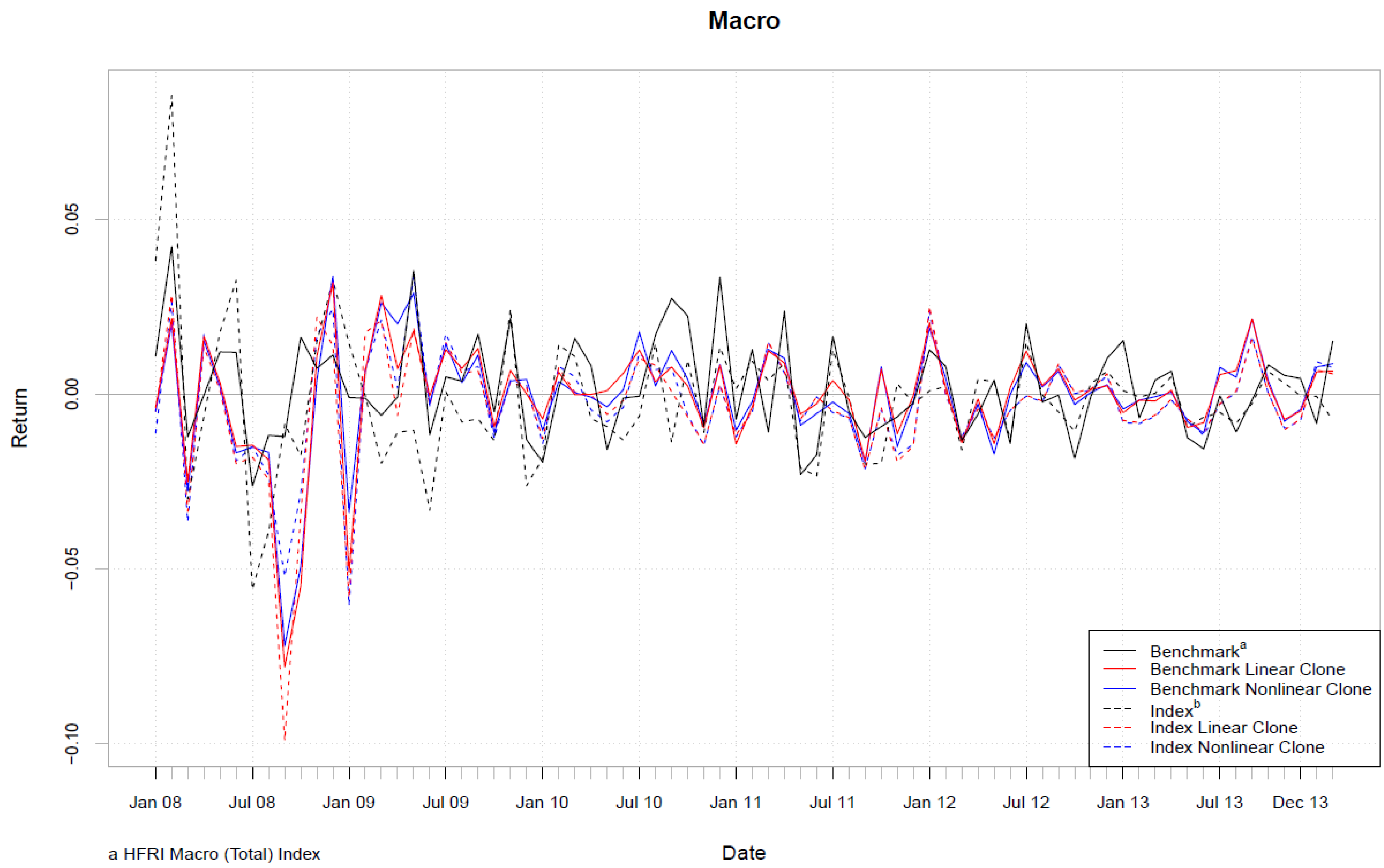
a HFRI Event−Driven (Total) Index
b HFRX Event Driven Index



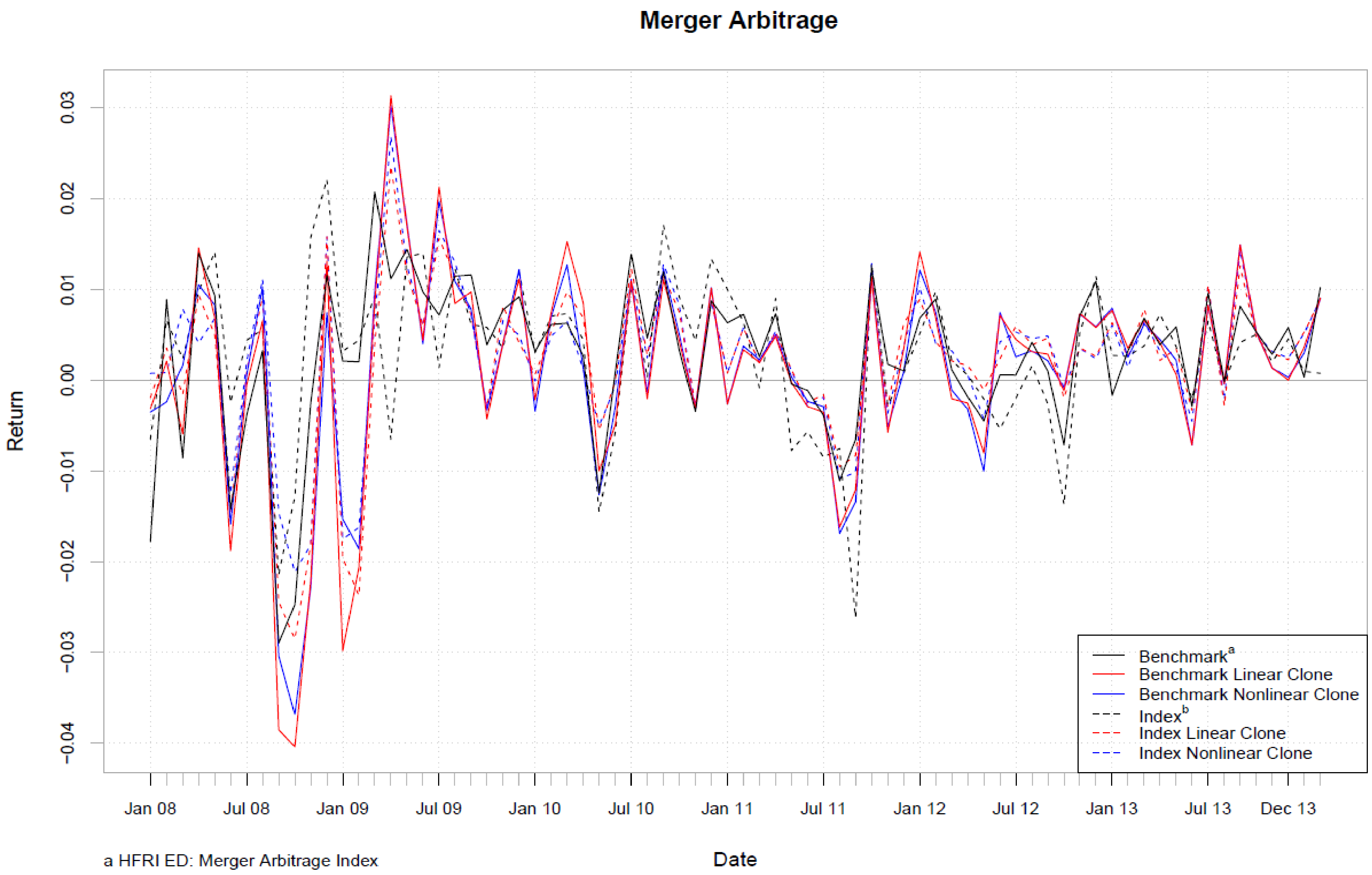
a HFRI Equity Hedge (Total) Index
b HFRX Equity Hedge Index



a HFRI EH: Equity Market Neutral Index
b HFRX EH: Equity Market Neutral Index

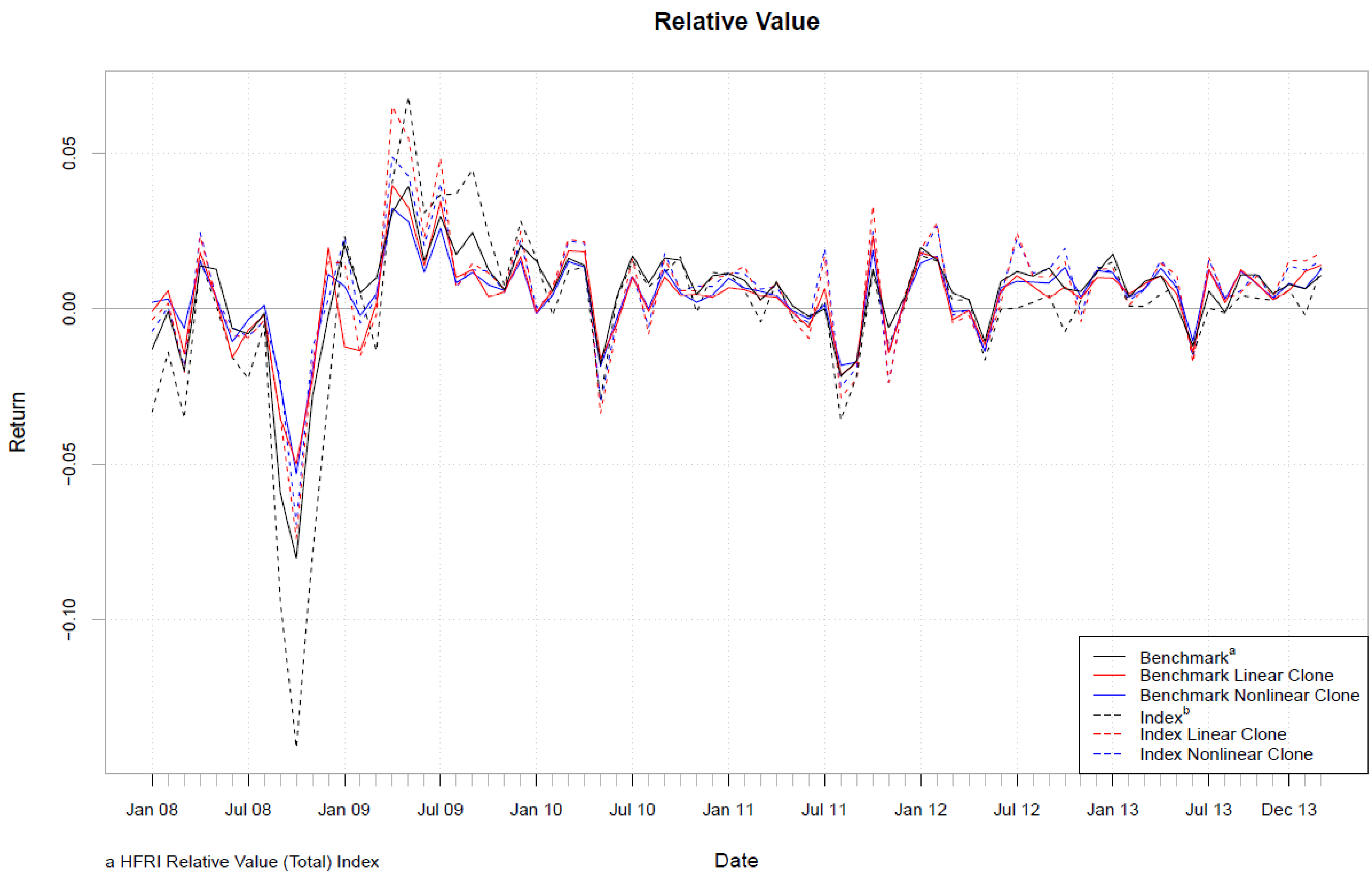


a HFRI Macro (Total) Index
b HFRX Macro/CTA Index



a HFRI ED: Merger Arbitrage Index

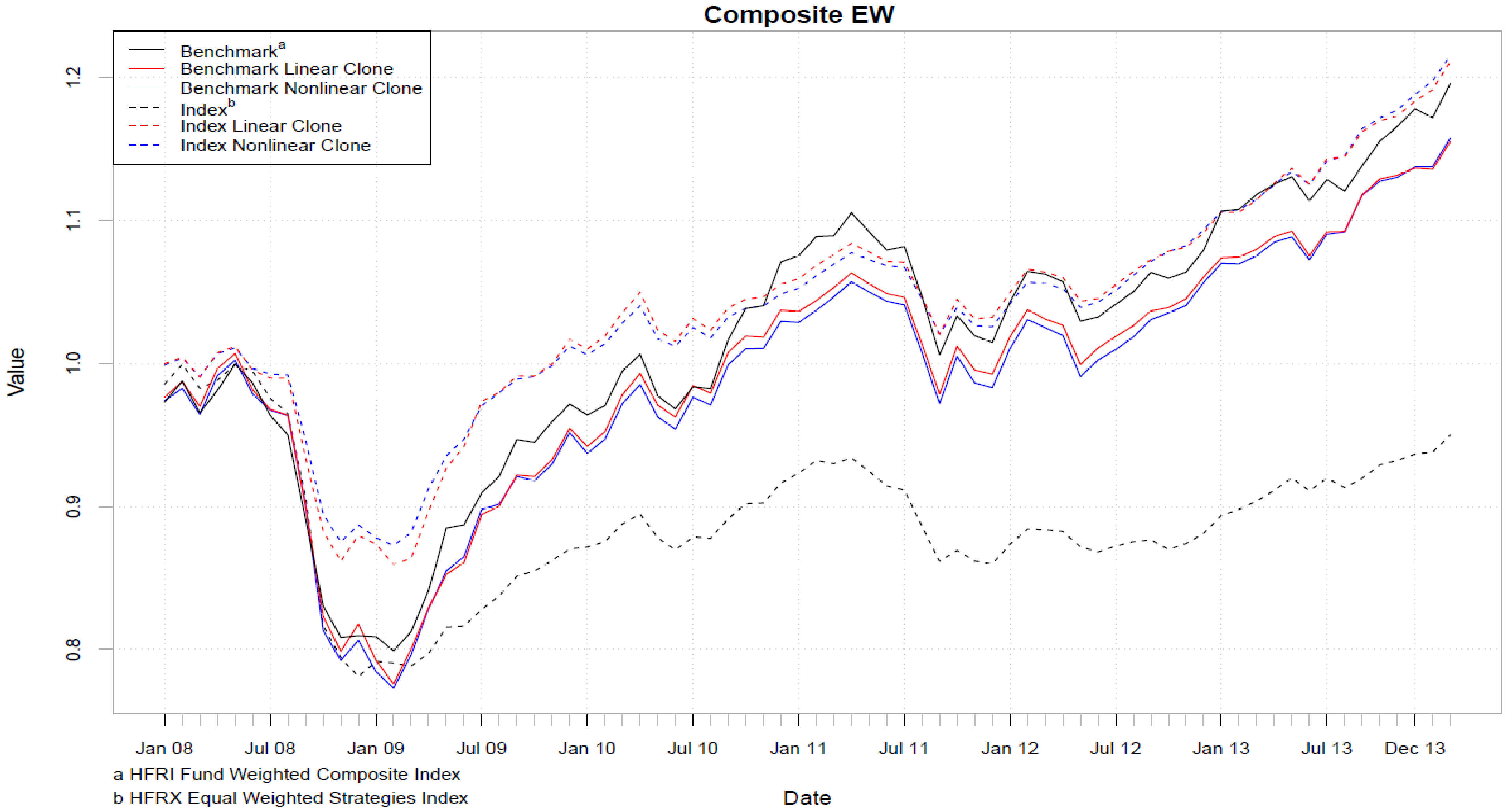
b HFRX ED: Merger Arbitrage Index

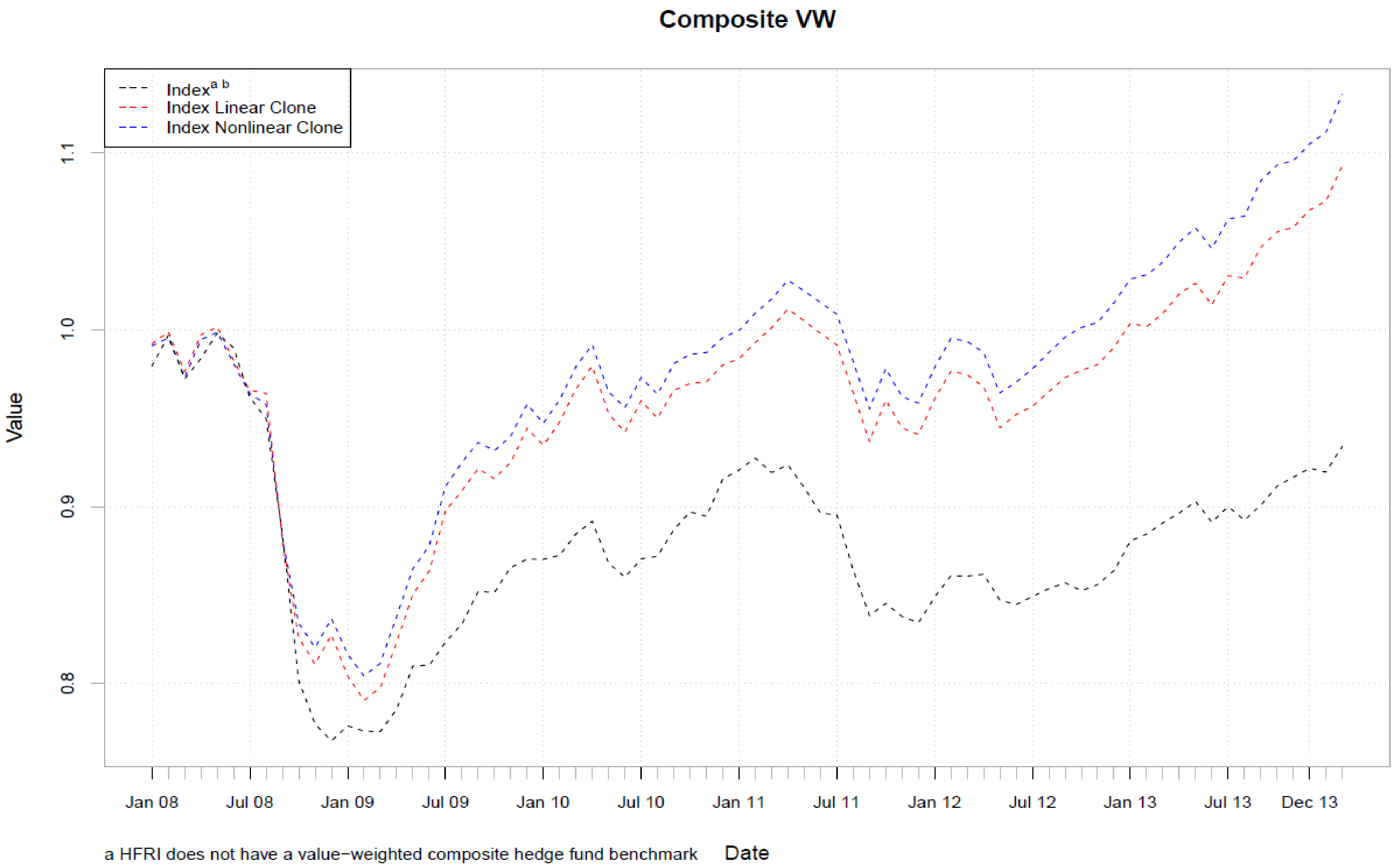


a HFRI Relative Value (Total) Index
b HFRX Relative Value Arbitrage Index

Figure 8.2 Cumulative Performance of HFRI Benchmarks, HFRX Indices and Replicating Portfolios

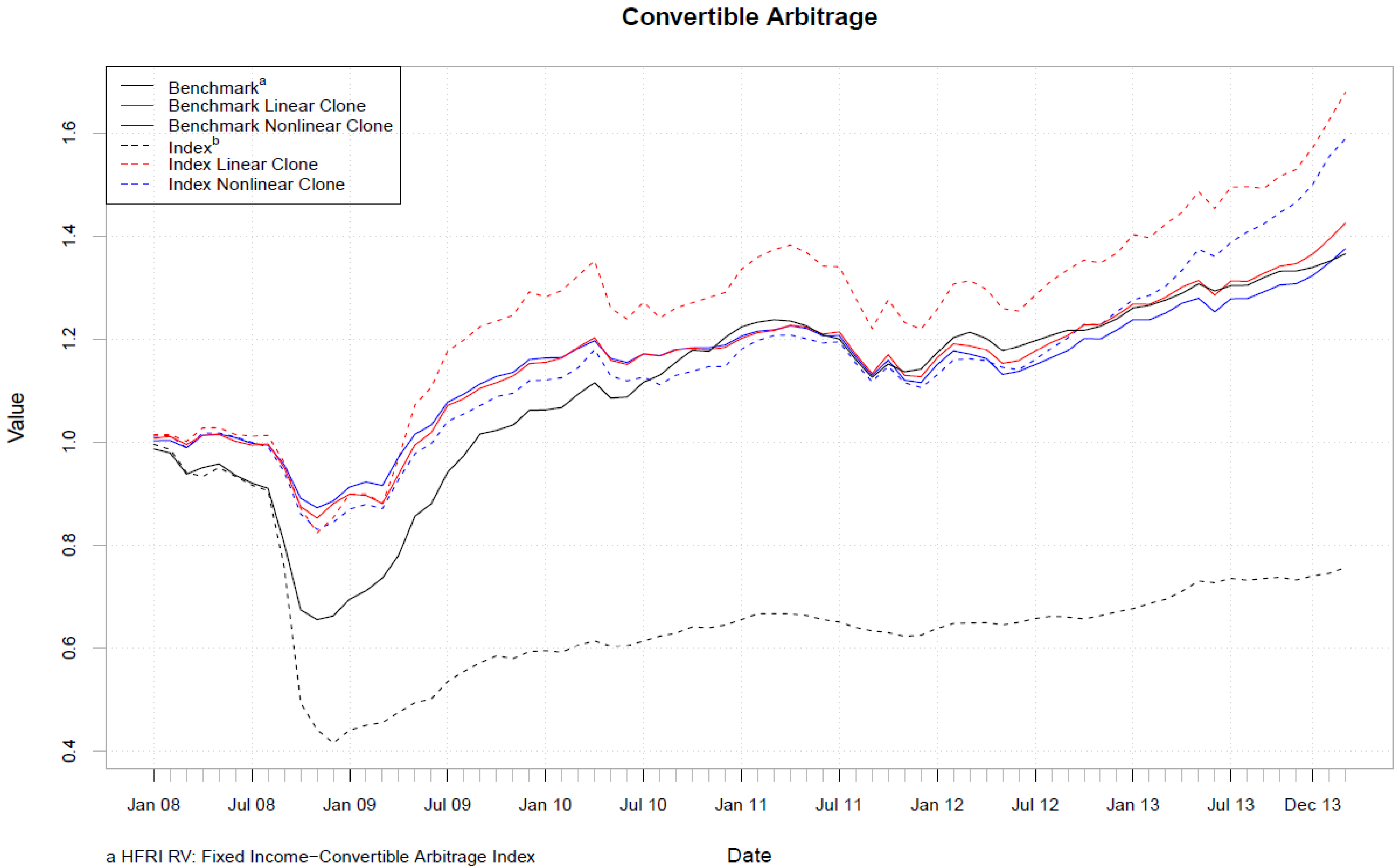
The graphs show cumulative performance of HFRI style benchmarks and HFRX style indices and their out-of-sample linear and nonlinear clones during the period from January 2008 to February 2014. Clones are constructed based on 14-factor models SLM14 and SGAML14 using rolling window procedure.



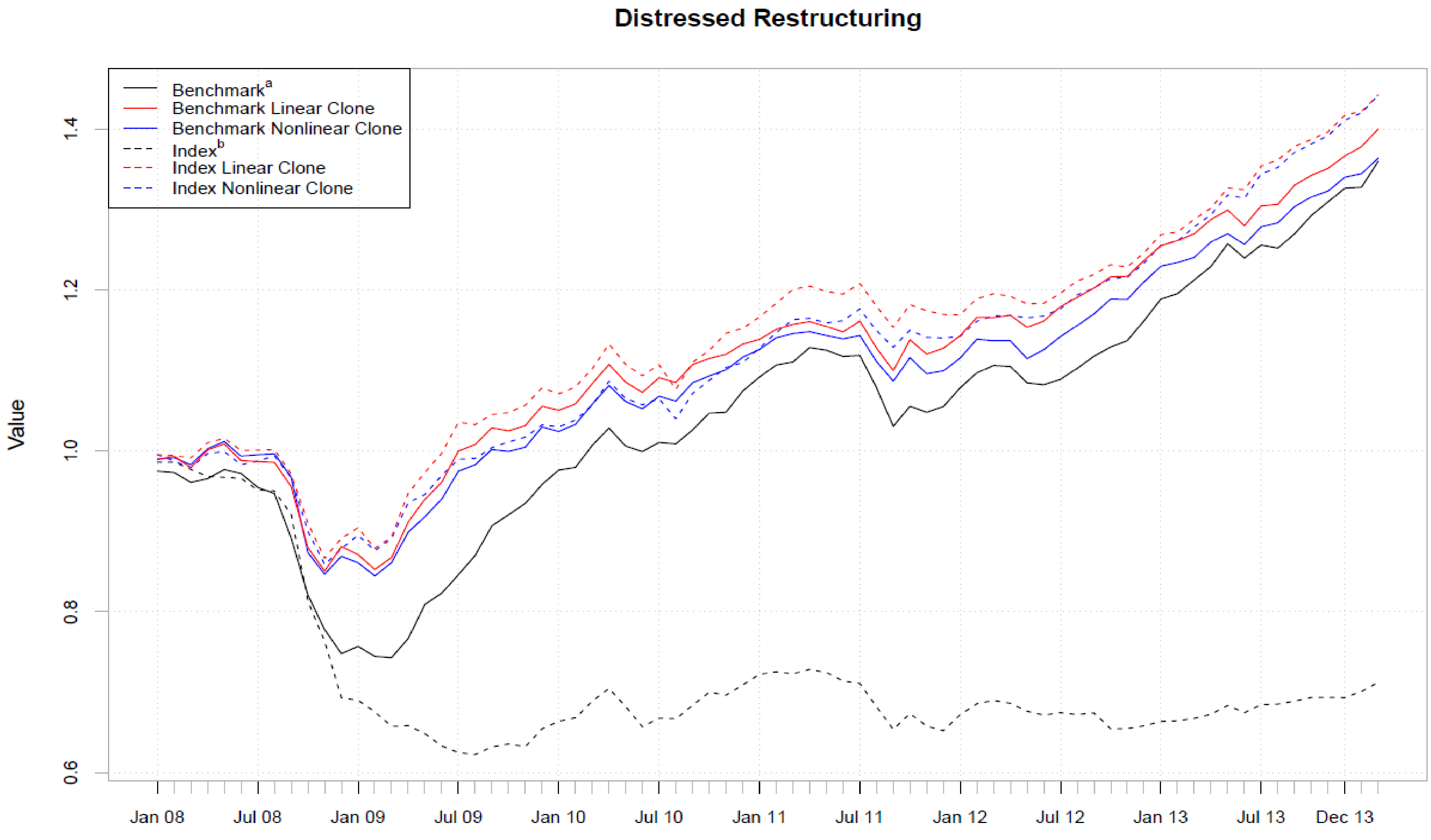


a HFRI does not have a value−weighted composite hedge fund benchmark

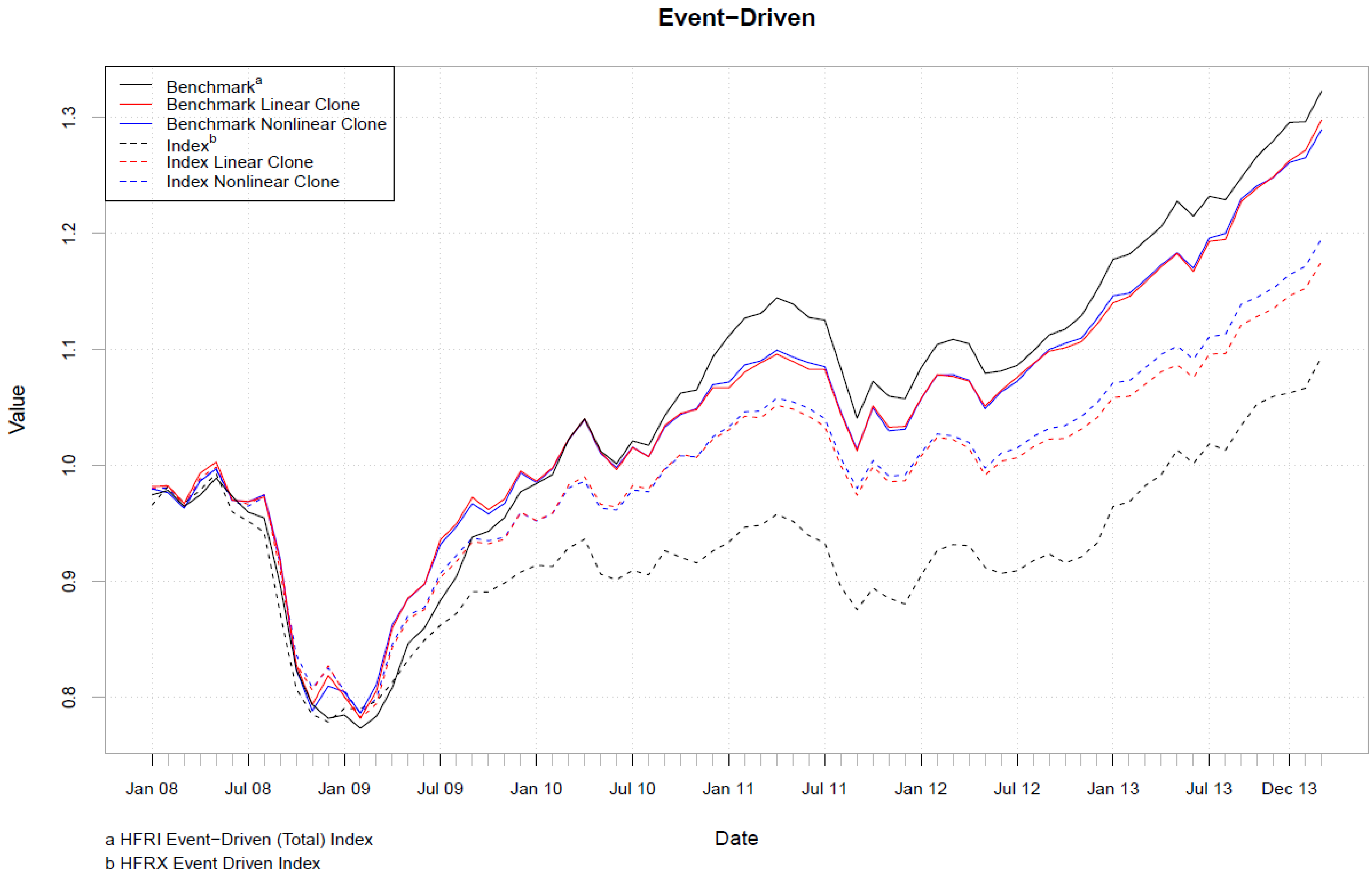
b HFRX Global Hedge Fund Index



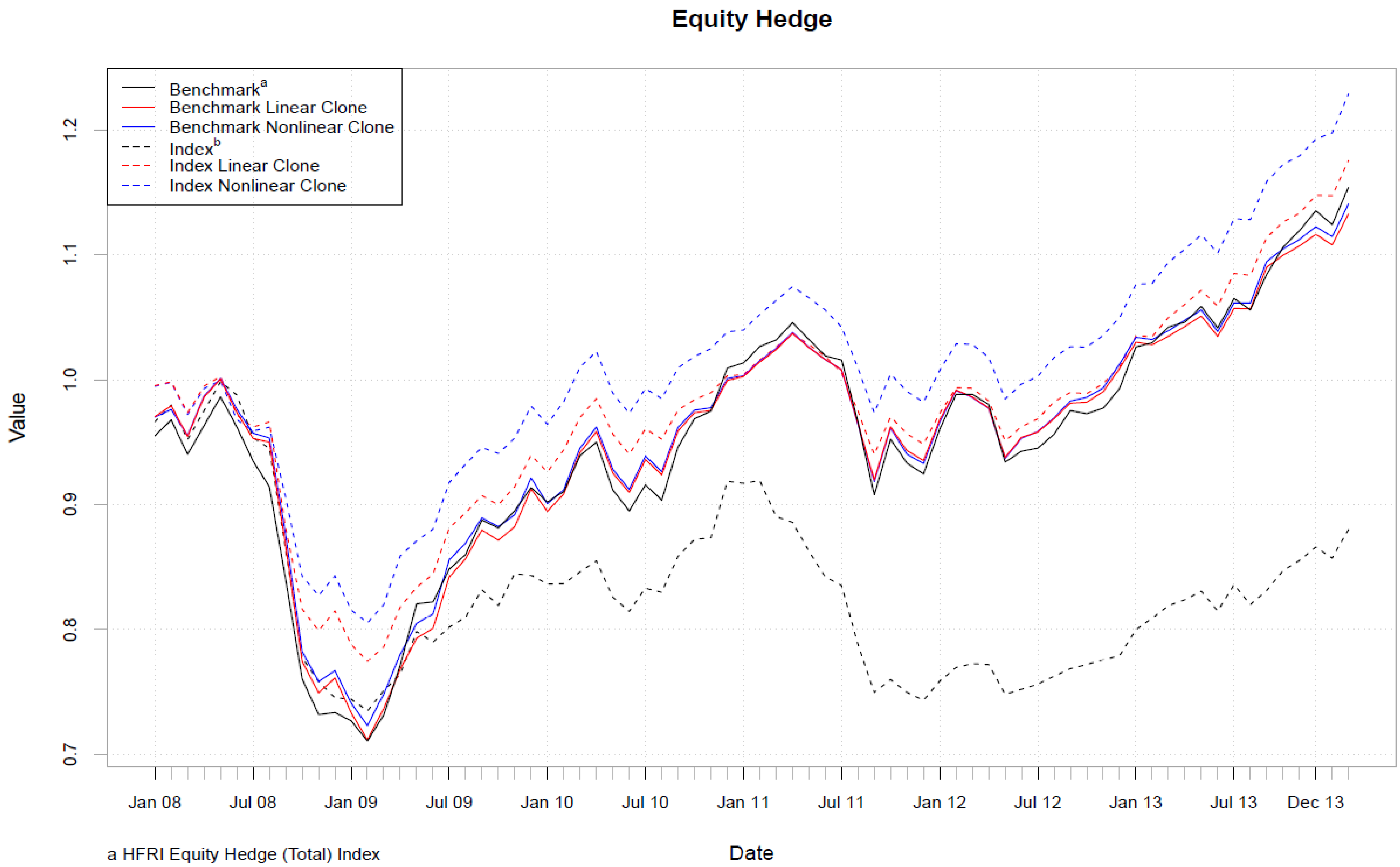
a HFRI RV: Fixed Income−Convertible Arbitrage Index
b HFRX RV: FI−Convertible Arbitrage Index



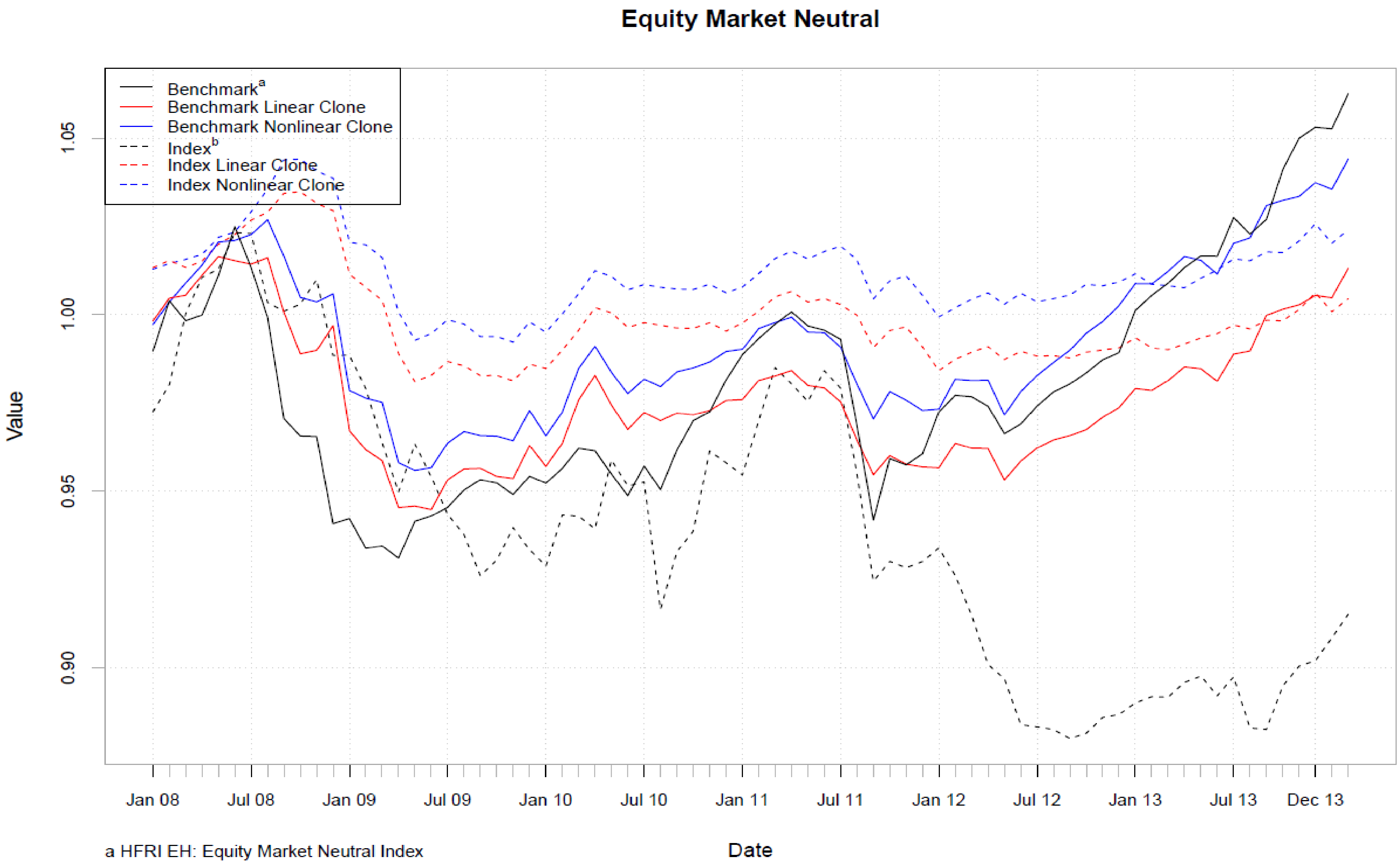
a HFRI ED: Distressed/Restructuring Index
b HFRX ED: Distressed Restructuring Index



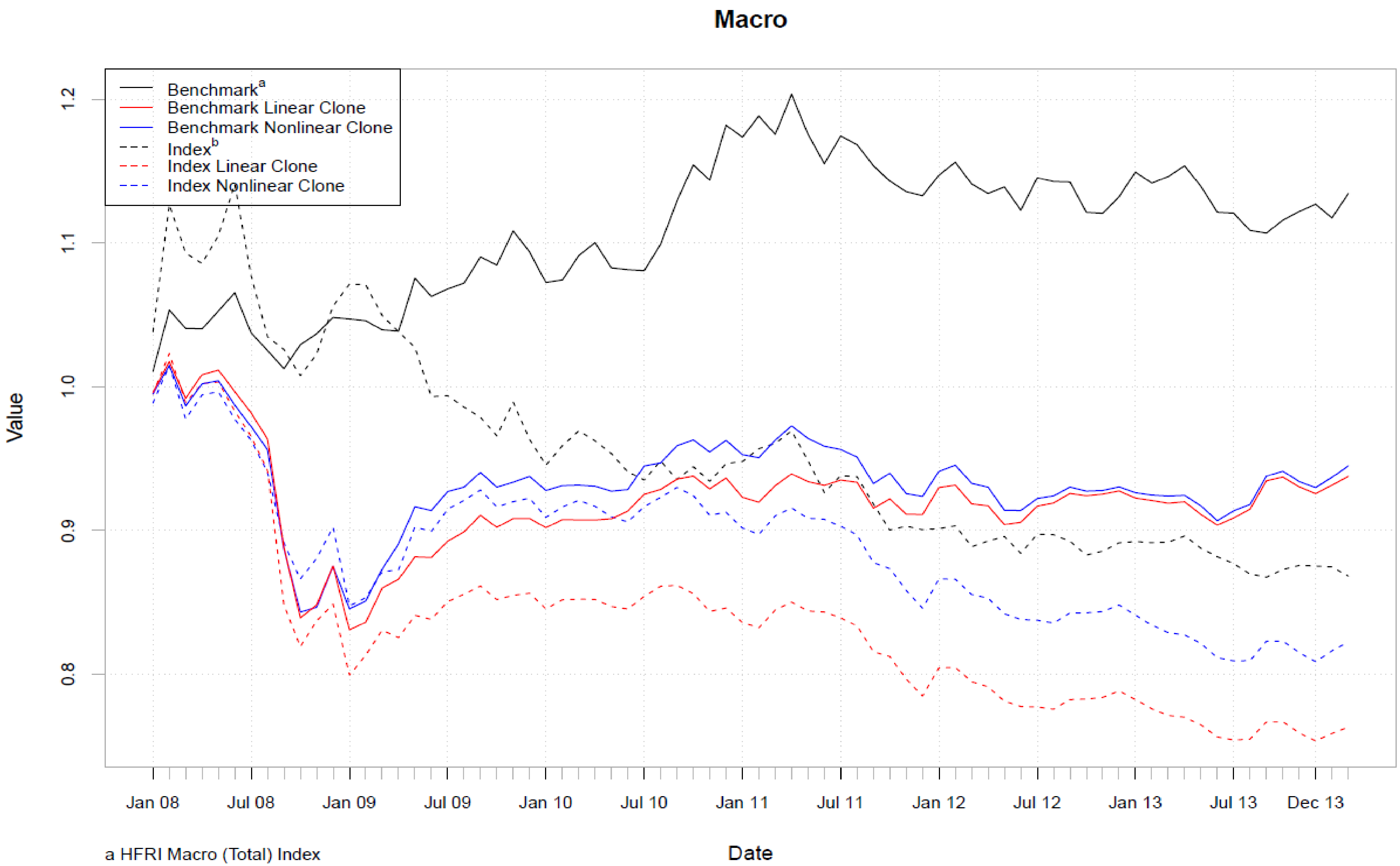
Event−Driven
Benchmark[a]
Benchmark Linear Clone
Benchmark Nonlinear Clone
Index[b]
Index Linear Clone
Index Nonlinear Clone
Value
1.3
1.2
1.1
1.0
0.9
0.8
Jan 08
Jul 08
Jan 09
Jul 09
Jan 10
Jul 10
Jan 11
Jul 11
Jan 12
Jul 12
Jan 13
Jul 13
Dec 13
Date
a HFRI Event−Driven (Total) Index
b HFRX Event Driven Index



a HFRI Equity Hedge (Total) Index
b HFRX Equity Hedge Index

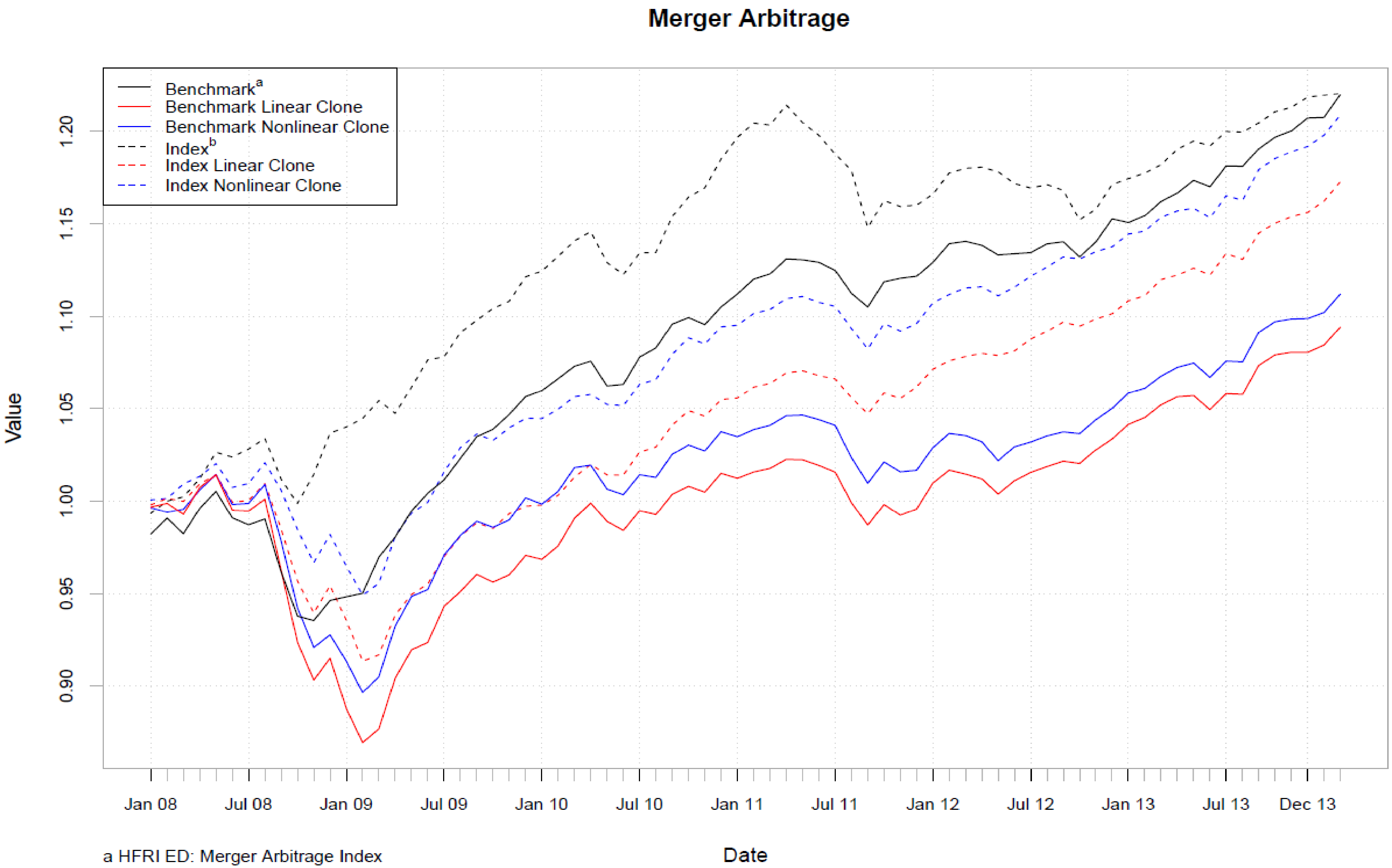


a HFRI EH: Equity Market Neutral Index
b HFRX EH: Equity Market Neutral Index

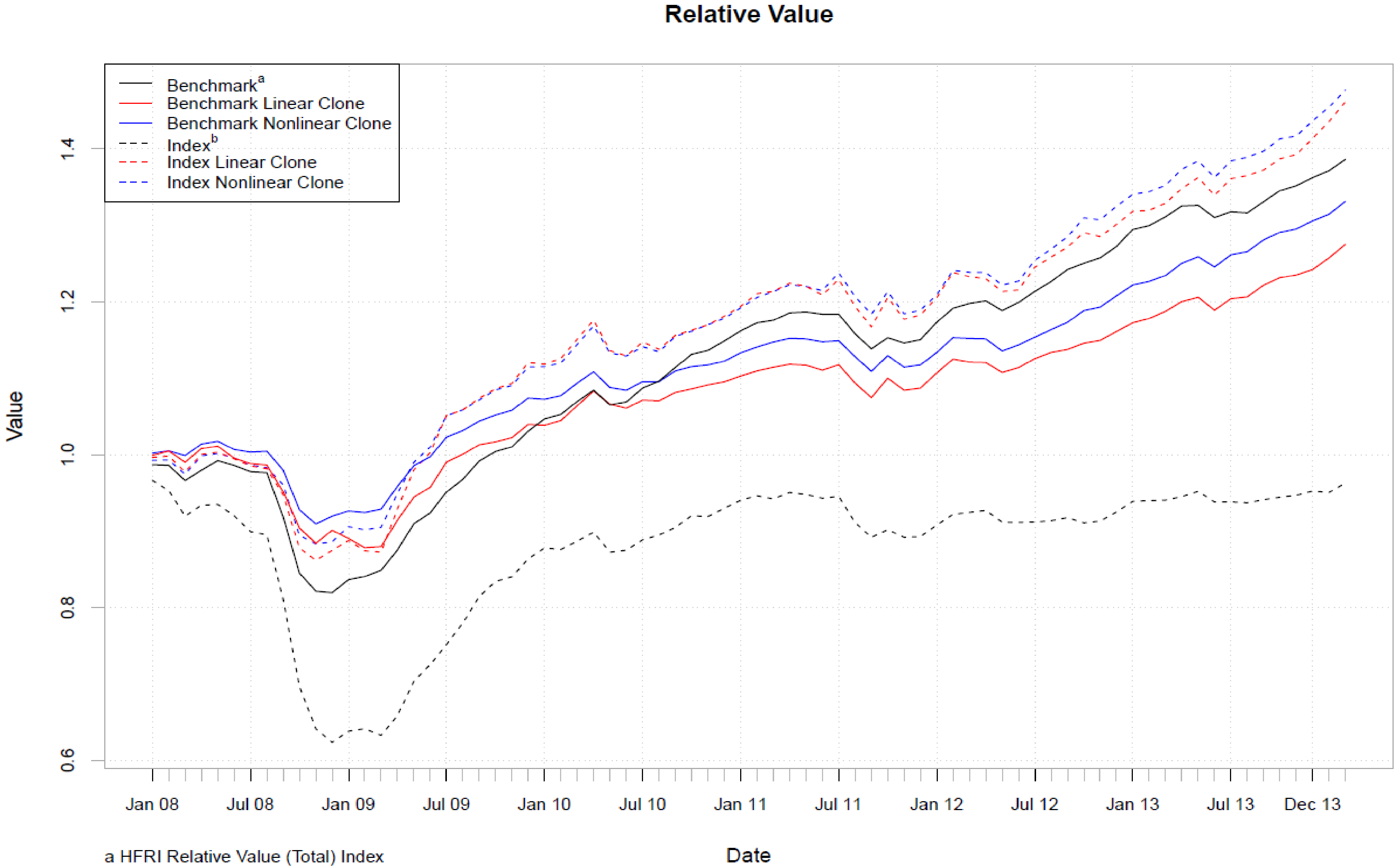


a HFRI Macro (Total) Index

b HFRX Macro/CTA Index



a HFRI ED: Merger Arbitrage Index
b HFRX ED: Merger Arbitrage Index



a HFRI Relative Value (Total) Index
b HFRX Relative Value Arbitrage Index

8.3 Relative Performance of HFR Replicating Portfolios

Another aspect of passive replicating strategies is their performance relatively to the benchmarks they purport to track. Accordingly, this section examines how closely two replicating approaches, the linear and the nonlinear, match various performance characteristics of their benchmarks. Proposed performance measures cover the first four moments of return distribution as well as the tail risk.

Table 8.4 presents the results of an out-of-sample performance analysis. Performance is evaluated using the Sharpe ratio, the modified Sharpe ratio, the Sortino ratio, the information ratio and the expected shortfall. The results pertaining to HFRI clones are discussed first, and then HFRX clones are examined. As seen from the table, in five styles out of nine (DS, EH, EMN, M, and MA) nonlinear HFRI clones match the risk-adjusted performance (Sharpe ratio, modified Sharpe ratio and Sortino ratio) of their benchmarks better than linear clones do. Average excess performance across all the styles is also lower in absolute value for nonlinear clones than for linear clones: the average excess Sharpe ratio is -0.088 for nonlinear clones and -0.152 for linear clones[124]; the average excess modified Sharpe ratio is -0.051 and -0.082 for nonlinear and linear clones respectively; and the average excess Sortino ratio is -0.037 and -0.057 accordingly. In several styles, particularly in the Equity Hedge and the Equity Market Neutral categories three risk-adjusted performance measures of nonlinear clone are particularly close to those of underlying benchmarks. The excess Sharpe ratio for nonlinear clones is just -0.007 and 0.004; the excess modified Sharpe

[124] See these values at the bottom of Table 8.4 in the group with heading “Avg.”, lines corresponding to HFRI Linear and Nonlinear clones

ratio is -0.008 and 0.000; and the excess Sortino ratio is -0.006 and -0.001 in the Equity Hedge and the Equity Market Neutral categories respectively. In other categories the risk-adjusted performance of linear and nonlinear clones is very close. For instance in the Convertible Arbitrage, the Event Driven, the Equal-Weighted composite and the Relative Value Arbitrage styles the difference in excess Sharpe ratios between the linear and the nonlinear clones is less than 0.1.

To test statistical significance of the differences in the risk-adjusted performance of clones and benchmarks, the Jobson and Korkie (1981) Sharpe ratio test is applied. With regards to other risk-adjusted measures there are no commonly used statistical tests at the moment. The Jobson and Korkie test reveals that the excess Sharpe ratio of both linear and nonlinear clones is not statistically different from zero in all styles but one (Merger Arbitrage). This is consistent with insignificant results on the difference between the raw returns of indices and clones in Section 8.2, Table 8.2. Statistically speaking therefore, neither raw nor risk-adjusted performance of most of the linear and nonlinear clones differs from their benchmarks. This is a very important finding, because it supports the feasibility of the concept of hedge fund replication. It provides empirical evidence that refined replication and variable selection techniques can mitigate concerns about poor quality of out-of-sample fit of the clones raised in earlier studies (Amenc et al., 2010).

Another important performance measure which simultaneously deals with the tracking accuracy and the relative performance is the information ratio (IR). It is defined as active return (return above the benchmark), divided by the tracking error. In five styles out of nine, including the Equal Weighted composite category, nonlinear HFRI clones have higher information ratio than their linear competitors. The average information ratio across all styles is also higher for nonlinear clones: it is -0.208 for nonlinear clones and -0.232 for linear clones. Higher information ratio can be interpreted as higher active return for the amount of risk taken. Risk in this case is measured by the tracking error and linked to the overall deviation from the benchmark. Rational investors always prefer index funds with higher information ratio.

Another characteristic of returns, which is particularly important for hedge funds, is the average tail risk or the expected shortfall. It is calculated as average loss below 95% VaR. The expected shortfall provides a glimpse of the negative left tail of the distribution. As seen from last two columns in Table 8.4 nonlinear clones are better than linear clones in terms of matching the expected shortfall of the underlying benchmarks in four styles out of nine as well as overall across all the styles. To provide a simple numerical example that could assist with the interpretation of results, consider an investment of $1 billion into an investment strategy that is designed to replicate the average performance of HFRI style benchmarks. If the expected shortfall of that strategy is the same as the average expected shortfall of linear and nonlinear HFRI clones, then its average loss could exceed $5.4 million and $5.5 million respectively in 5 of 100 cases, whereas the average loss of HFRI benchmarks would be $5.7 million. The example illustrates that overall HFRI linear clones slightly underestimate the tail risk comparing with nonlinear replicating strategies. It is not surprising, given that the linear approach is not meant to capture nonlinear risk exposures which often drive extreme losses.

Turning the discussion to clones of investable indices, Table 8.4 reports the results of the performance analysis of HFRX linear and nonlinear clones. The single most striking observation that emerges from the table is related to absolute performance of linear and particularly nonlinear clones which is far better than performance of HFRX portfolios in most of the styles. Both types of clones have positive excess Sharpe ratio, excess modified Sharpe ratio and excess Sortino ratio in all the styles except the Macro and the Merger Arbitrage categories. The excess Sharpe ratio is highly statistically significant in five styles. The average Sharpe ratio of linear and nonlinear clones is positive 0.456 and 0.594 respectively, while the average Sharpe ratio of HFRX indices is negative 0.073. Similar results are noted with other performance measures: the average modified Sharpe ratio and the Sortino ratio of clones is positive and negative or close to zero for HFRX portfolio.

The major takeaway point from these results is a clear failure of HFRX indices to provide comparable performance with HFRI benchmarks and their very large tracking error. One of possible explanations to this result is the “Groucho Marx” effect mentioned above. As a result, there is hardly any value to potential investors in replicating portfolios of investable HFRX indices[125]. Instead, the results show that HFRI indices which are widely used as hedge fund benchmarks in the industry can be replicated synthetically and with much lower tracking error than HFRX indices.

The next section provides the results of some robustness tests.

[125] Nevertheless, as of July 2014 at least one replicator fund of HFRX indices was offered in the market by one of the largest investment banks

Table 8.4 Performance Characteristics of HFRI and HFRX Indices and Replicating Portfolios

The table presents the annualized Sharpe ratio; the excess Sharpe ratio of linear and nonlinear HFRI/HFRX clones over benchmark (Δ*Sharpe*) and the associated t-statistic; the modified Sharpe ratio (*Mod. Sharpe*), the excess modified Sharpe ratio; the Sortino ratio; the excess Sortino ratio (Δ*Sortino*); the annualized information ratio (*Inform. Ratio*); the expected shortfall (*ES*) at 95% confidence level; and the excess expected shortfall (Δ*ES*). Values of Δ*Sharpe* marked with *, **, and *** are significant at the 10, 5, and 1% levels, respectively.

Style	Index Name	Type	Sharpe	ΔSharpe	t-stat	Mod. Sharpe	ΔMod. Sharpe	Sortino	ΔSortino	Inform. Ratio	ES	ΔES
CA	HFRI	Index	0.451			0.254		0.189			-0.141	
		Linear	0.767	0.316	-1.224	0.504	0.250	0.343	0.154	0.117	-0.058	0.083
		Nonlinear	0.774	0.323	-1.231	0.507	0.253	0.347	0.158	0.019	-0.050	0.091
	HFRX	Index	-0.252			-0.124		-0.047			-0.141	
		Linear	0.795	1.047***	-3.296	0.579	0.703	0.387	0.434	0.966	-0.067	0.074
		Nonlinear	0.967	1.22***	-4.183	0.622	0.746	0.426	0.472	0.943	-0.062	0.078
DS	HFRI	Index	0.656			0.383		0.270			-0.059	
		Linear	0.848	0.192	-0.662	0.529	0.146	0.366	0.096	0.102	-0.058	0.001
		Nonlinear	0.776	0.120	-0.374	0.449	0.066	0.311	0.042	0.010	-0.075	-0.017
	HFRX	Index	-0.622			-0.288		-0.189			-0.090	
		Linear	0.949	1.571***	-4.107	0.628	0.916	0.422	0.611	1.533	-0.049	0.041
		Nonlinear	1.029	1.651***	-4.056	0.640	0.927	0.429	0.618	1.653	-0.052	0.038
ED	HFRI	Index	0.624			0.361		0.257			-0.059	
		Linear	0.528	-0.096	0.494	0.311	-0.050	0.223	-0.033	-0.086	-0.073	-0.015
		Nonlinear	0.520	-0.104	0.576	0.297	-0.063	0.214	-0.042	-0.125	-0.079	-0.020
	HFRX	Index	0.211			0.111		0.089			-0.058	
		Linear	0.358	0.147	-0.665	0.201	0.090	0.149	0.060	0.297	-0.070	-0.011
		Nonlinear	0.409	0.198	-0.902	0.232	0.121	0.169	0.080	0.380	-0.065	-0.007
EH	HFRI	Index	0.233			0.133		0.110			-0.072	
		Linear	0.210	-0.023	0.198	0.115	-0.018	0.097	-0.012	-0.103	-0.078	-0.006
		Nonlinear	0.225	-0.007	0.081	0.125	-0.008	0.103	-0.006	-0.065	-0.077	-0.005
	HFRX	Index	-0.229			-0.118		-0.065			-0.077	
		Linear	0.337	0.566**	-2.221	0.185	0.303	0.141	0.206	0.924	-0.065	0.012
		Nonlinear	0.461	0.69***	-2.673	0.270	0.387	0.196	0.262	1.029	-0.051	0.025
EMN	HFRI	Index	0.309			0.170		0.122			-0.024	
		Linear	0.093	-0.216	0.512	0.049	-0.121	0.038	-0.084	-0.270	-0.022	0.003
		Nonlinear	0.313	0.004	0.001	0.170	0.000	0.121	-0.001	-0.100	-0.019	0.005
	HFRX	Index	-0.344			-0.184		-0.117			-0.030	
		Linear	0.047	0.390	-0.703	0.026	0.210	0.020	0.137	0.348	-0.014	0.015
		Nonlinear	0.237	0.581	-1.043	0.133	0.317	0.093	0.211	0.419	-0.014	0.016
EW	HFRI	Index	0.409			0.239		0.176			-0.053	
		Linear	0.314	-0.095	0.603	0.174	-0.066	0.133	-0.043	-0.203	-0.062	-0.009
		Nonlinear	0.310	-0.099	0.621	0.169	-0.070	0.130	-0.046	-0.190	-0.071	-0.018
	HFRX	Index	-0.135			-0.065		-0.034			-0.075	
		Linear	0.564	0.699***	-3.140	0.330	0.395	0.233	0.267	1.153	-0.046	0.029
		Nonlinear	0.652	0.788***	-3.661	0.376	0.441	0.262	0.296	1.268	-0.042	0.033
M	HFRI	Index	0.420			0.308		0.221			-0.023	
		Linear	-0.180	-0.600	1.310	-0.089	-0.396	-0.052	-0.273	-0.493	-0.061	-0.038
		Nonlinear	-0.165	-0.585	1.316	-0.085	-0.393	-0.049	-0.270	-0.503	-0.056	-0.033
	HFRX	Index	-0.347			-0.270		-0.134			-0.024	
		Linear	-0.689	-0.343	0.800	-0.316	-0.046	-0.213	-0.079	-0.262	-0.080	-0.056
		Nonlinear	-0.576	-0.229	0.499	-0.292	-0.022	-0.192	-0.058	-0.117	-0.048	-0.024
MA	HFRI	Index	1.102			0.690		0.469			-0.021	
		Linear	0.356	-0.746**	2.345	0.199	-0.491	0.142	-0.327	-0.687	-0.034	-0.012
		Nonlinear	0.466	-0.635**	2.045	0.273	-0.417	0.191	-0.278	-0.664	-0.029	-0.007
	HFRX	Index	1.119			0.747		0.511			-0.019	
		Linear	0.830	-0.289	0.588	0.497	-0.250	0.336	-0.175	-0.213	-0.023	-0.004
		Nonlinear	1.078	-0.041	0.084	0.743	-0.003	0.494	-0.018	-0.053	-0.019	0.001
RVA	HFRI	Index	0.907			0.519		0.348			-0.062	
		Linear	0.811	-0.096	0.380	0.524	0.005	0.357	0.008	-0.465	-0.037	0.025
		Nonlinear	1.098	0.191	-0.921	0.690	0.171	0.461	0.112	-0.253	-0.039	0.023
	HFRX	Index	-0.061			-0.031		-0.003			-0.114	
		Linear	0.916	0.977***	-3.952	0.639	0.670	0.427	0.431	1.181	-0.052	0.062
		Nonlinear	1.091	1.152***	-4.158	0.729	0.760	0.493	0.497	1.177	-0.050	0.064
Avg.	HFRI	Index	0.568			0.340		0.240			-0.057	
		Linear	0.416	-0.152	1.003	0.257	-0.082	0.183	-0.057	-0.232	-0.054	0.003
		Nonlinear	0.480	-0.088	0.566	0.288	-0.051	0.203	-0.037	-0.208	-0.055	0.002
	HFRX	Index	-0.073			-0.025		0.001			-0.070	
		Linear	0.456	0.53**	-2.184	0.308	0.332	0.211	0.210	0.659	-0.052	0.018
		Nonlinear	0.594	0.668**	-2.710	0.384	0.408	0.263	0.262	0.744	-0.045	0.025

8.4 Robustness Checks

This section examines the robustness of results in terms of the choice of hedge fund benchmarks and risk factor set. Specifically, the replication analysis is carried out for TASS indices, which are used in the first part of this thesis. Also, in addition to clones based on the 14-factor models (SLM14 and SGAML14), clones based on the six-factor models (HL6 and GAML6) are constructed and evaluated.

Table 8.5 compares the returns of TASS hedge fund style indices and four replicating portfolios, two linear and two nonlinear. It shows the mean and the median values of the difference between clone returns and index returns. As seen from Panel A, the 14-factor nonlinear clones (SGAML14) have lower excess return than the 14-factor linear clones (SLM14) in four styles out of twelve. The result is stronger for six-factor models: clones based on the nonlinear model GAML6 have lower positive excess returns in all but one style. The average excess return across all the styles of the nonlinear GAML6 clones (0.19%) is 7b.p. p.a. less than that of the linear HL6 clones (0.26%). Differences between the six and 14-factor clones also suggest that variable selection helps to improve the accuracy of the replication: the excess return is significantly different from zero in five styles for six-factor clones and only in two styles for 14-factor clones. The results with the median excess return in Panel B are qualitatively similar, but the difference between the nonlinear and the linear clones is smaller.

Table 8.5 Difference in Returns of TASS Indices and Replicating Portfolios

The table shows the mean (median) difference in monthly returns, ΔR, of TASS indices and their clones with associated p-values of two-sided heteroscedastic t-test (Wilcoxon signed-rank test) over the out-of-sample period January 2008 – February 2014. The clones are constructed using a rolling window procedure and the linear models HL6 and SLM14 and the nonlinear models GAML6 and SGAML14. Values of ΔR significant at 5% level are shown in bold.

Panel A: Two-Sided Heteroscedastic t-Test

Model	HL6		GAML6		SLM14		SGAM14	
Style	ΔR	P-value	ΔR	P-value	ΔR	P-value	ΔR	P-value
CA	0.0009	0.676	-0.0001	0.970	0.0009	0.622	0.0011	0.549
DSB	-0.0048	0.210	-0.0042	0.277	-0.0050	0.152	-0.0034	0.343
EM	**0.0080**	0.001	**0.0071**	0.003	-0.0001	0.949	-0.0002	0.925
EMN	0.0014	0.209	-0.0002	0.875	0.0014	0.249	0.0007	0.576
ED	**0.0059**	0.000	**0.0046**	0.000	**0.0030**	0.025	**0.0032**	0.011
FIA	0.0002	0.921	0.0002	0.914	0.0005	0.753	0.0005	0.768
GM	**0.0059**	0.004	**0.0051**	0.009	0.0034	0.092	0.0034	0.089
LSE	**0.0042**	0.007	**0.0036**	0.024	**0.0025**	0.031	**0.0023**	0.038
MF	0.0016	0.672	0.0003	0.926	0.0011	0.798	0.0004	0.925
MS	0.0026	0.077	0.0018	0.210	0.0019	0.205	0.0019	0.152
FoF	0.0012	0.373	0.0008	0.539	-0.0010	0.353	-0.0010	0.326
HFC	**0.0040**	0.005	**0.0035**	0.007	0.0013	0.291	0.0016	0.189

Panel B: Wilcoxon Signed-Rank Test

Model	HL6		GAML6		SLM14		SGAM14	
Style	ΔR	P-value	ΔR	P-value	ΔR	P-value	ΔR	P-value
CA	0.0024	0.121	0.0024	0.178	0.0033	0.066	**0.0031**	0.044
DSB	-0.0038	0.257	-0.0048	0.325	-0.0021	0.217	0.0004	0.641
EM	**0.0080**	0.001	**0.0095**	0.002	0.0003	0.974	0.0006	0.932
EMN	0.0026	0.051	0.0012	0.563	0.0018	0.106	0.0016	0.228
ED	**0.0080**	0.000	**0.0056**	0.000	**0.0040**	0.003	**0.0045**	0.002
FIA	0.0028	0.178	0.0034	0.116	0.0009	0.296	0.0017	0.197
GM	**0.0071**	0.004	**0.0049**	0.013	0.0015	0.132	0.0034	0.133
LSE	**0.0039**	0.016	**0.0039**	0.030	0.0009	0.075	0.0013	0.085
MF	-0.0003	0.760	-0.0024	0.951	-0.0010	0.858	0.0005	0.936
MS	**0.0024**	0.040	0.0025	0.068	0.0029	0.067	**0.0032**	0.044
FoF	0.0016	0.302	0.0020	0.457	-0.0015	0.275	-0.0013	0.334
HFC	**0.0040**	0.004	**0.0048**	0.008	0.0022	0.151	0.0022	0.131

Next, Table 8.6 presents tracking efficiency measures for TASS hedge fund style replicating portfolios. Statistics include the annualized tracking error, the mean absolute error, the annualized geometric average excess return and the cumulative excess return. As observed from the table, on average, the tracking error of both the six-factor and 14-factor nonlinear clones is 10b.p. p.a. less than the tracking error of linear clones. Average value of the MAE of nonlinear clones is less than the MAE of linear clones by 6b.p. and 3b.p. monthly for six- and 14-factor clones respectively. The better tracking accuracy of nonlinear clones is also supported by lower tracking error and MAE of nonlinear clones of value-weighted composite hedge fund index (HFC). Overall, the six- and the 14-factor nonlinear clones are better than linear clones in terms of lower tracking error in eight styles out of twelve; and in terms of lower MAE they are better in all twelve styles and in eleven styles respectively.

To see how well clones are able to mimic hedge fund style returns Figure 8.3 provide graphs with the time-series of returns of indices and four clones. It can been seen that clones track indices reasonably well in most of the styles except the Equity Market Neutral, the Global Macro and the Managed Futures categories where the deviation in monthly returns is large.

Furthermore, in order to determine whether the difference, due to tracking error, between the returns of linear and nonlinear clones and the indices is of an economically significant magnitude, it is necessary to analyse the measures of excess performance. In general, the figures on the absolute and the cumulative excess returns in Table 8.6 reveal that TASS clones, similar to clones of HFRI indices, underperform their benchmarks. Excess returns are negative for most of the styles. However, comparing between the six-factor linear and nonlinear clones, on average the underperformance of nonlinear clones is 8b.p. p.a. less than the underperformance of linear competitors (-2.4% against -3.2% p.a.), while the difference in cumulated excess returns is even higher and reaches 4.4% (-13.1% against

17.5%). There is no clear winner among the 14-factor models: the average excess return is -1.2% p.a. and both clones outperform each other in terms of having lower cumulative excess return in five different styles out of twelve.

Additionally, Figure IX.1 given in Appendix IX displays cumulative performance graphs. They demonstrate that the 14-factor nonlinear clones trail cumulative performance of TASS indices better than linear clones do most of the time at least in seven styles out of twelve (DSB, EMN, ED, FIA, GM, LSE, MS), while the six-factor nonlinear model is better in ten styles (DSB, EM, EMN, ED, GM, LSE, MF, MS, FoF, HFC).

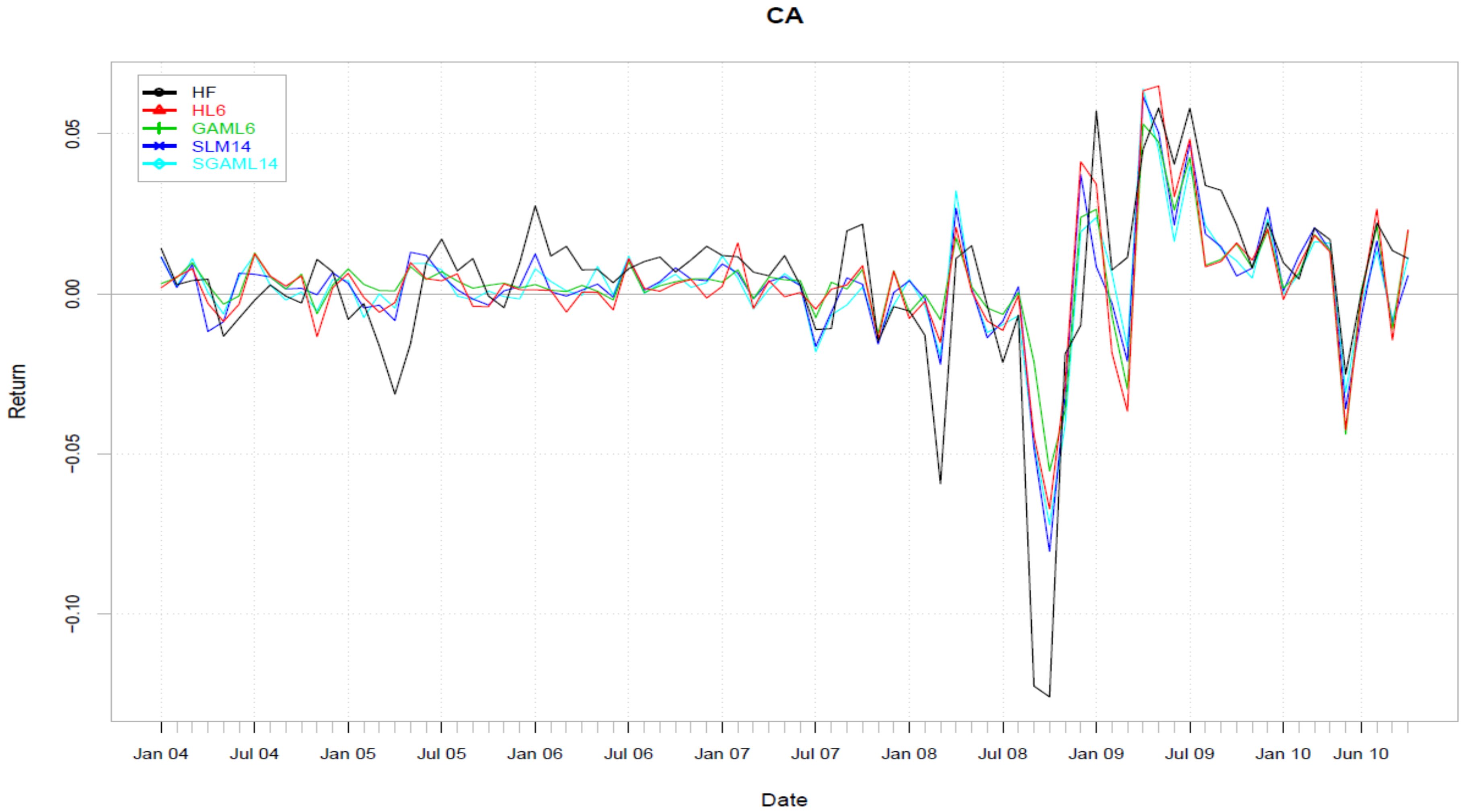
Table 8.6 Tracking Accuracy of TASS Replicating Portfolios

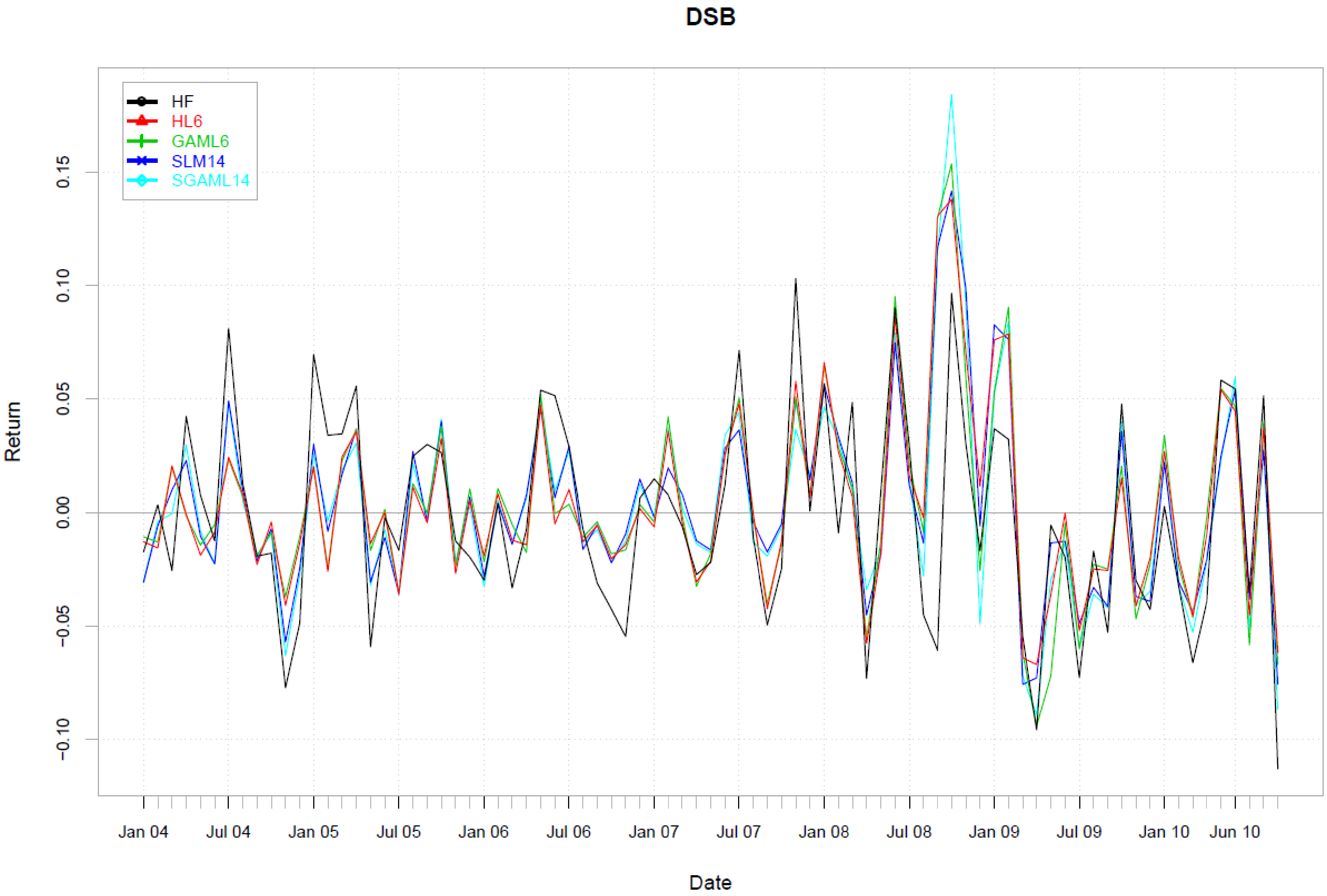
The table presents out-of-sample annualized tracking error, mean absolute error (MAE), annualized geometric average excess return (AER) and cumulative excess return (CER) of four clone portfolios of TASS hedge fund style indices during the period from January 2004 to September 2010. Clones are constructed using two six-factor models without variable selection, the linear model HL6 and the nonlinear model GAML6, and two 14-factor models, the linear model SLM14 and the nonlinear model SGAML14, through a rolling window procedure. The bottom line in the table contains the average value across all the styles. The lowest value of the tracking measures among four clones for each hedge fund style is shown in bold type.

Style	Tracking Error				Mean Absolute Error				Average Excess Return				Cumulative Excess Return			
Model	**HL6**	**GAML6**	**SLM14**	**SGAM14**	**HL6**	**GAML6**	**SLM14**	**SGAM14**	**HL6**	**GAML6**	**SLM14**	**SGAM14**	**HL6**	**GAML6**	**SLM14**	**SGAM14**
CA	0.064	0.068	**0.058**	**0.058**	0.0128	0.0126	0.0115	**0.0114**	-0.012	**-0.001**	-0.013	-0.015	-0.081	**-0.008**	-0.083	-0.097
DSB	0.118	0.120	**0.109**	0.110	0.0241	0.0238	0.0220	**0.0218**	0.052	0.044	0.056	**0.035**	0.407	0.341	0.444	**0.263**
EM	0.079	0.075	0.060	**0.057**	0.0181	0.0176	0.0132	**0.0126**	-0.094	-0.084	**0.000**	**0.000**	-0.488	-0.448	**-0.002**	0.003
EMN	**0.034**	0.035	0.038	0.037	0.0072	**0.0067**	0.0078	0.0070	-0.017	**0.002**	-0.018	-0.009	-0.109	**0.010**	-0.112	-0.057
ED	0.046	0.042	0.043	**0.040**	0.0109	0.0099	0.0094	**0.0090**	-0.069	-0.055	**-0.037**	-0.038	-0.383	-0.317	-0.223	**-0.231**
FIA	0.063	0.062	0.053	**0.051**	0.0120	0.0110	0.0103	**0.0098**	**-0.004**	**-0.004**	-0.008	-0.007	**-0.029**	**-0.029**	-0.051	-0.047
GM	0.065	**0.061**	0.063	0.063	0.0148	0.0138	**0.0133**	0.0134	-0.070	-0.061	**-0.042**	**-0.042**	-0.389	-0.344	**-0.252**	**-0.252**
LSE	0.049	0.050	0.037	**0.035**	0.0112	0.0110	0.0083	**0.0082**	-0.050	-0.044	-0.031	**-0.028**	-0.295	-0.259	-0.189	**-0.176**
MF	0.118	**0.113**	0.128	0.128	0.0285	**0.0275**	0.0299	0.0295	-0.026	**-0.010**	-0.021	-0.013	-0.164	**-0.068**	-0.132	-0.083
MS	0.045	0.043	0.045	**0.041**	0.0104	0.0095	0.0101	**0.0093**	-0.032	**-0.022**	-0.023	-0.024	-0.190	**-0.133**	-0.142	-0.145
FoF	0.042	0.040	0.035	**0.033**	0.0095	0.0093	0.0074	**0.0072**	-0.015	**-0.010**	0.012	0.012	-0.098	**-0.068**	0.083	0.084
HFC	0.045	0.041	0.039	**0.037**	0.0104	0.0097	0.0086	**0.0083**	-0.047	-0.042	**-0.016**	-0.020	-0.280	-0.252	**-0.106**	-0.125
Average	0.064	0.063	0.059	**0.058**	0.0141	0.0135	0.0126	**0.0123**	-0.032	-0.024	**-0.012**	**-0.012**	-0.175	-0.131	**-0.064**	-0.072

Figure 8.3 Time Series Returns of TASS Hedge Fund Indices and Replicating Portfolios

The graphs show returns of TASS hedge fund style indices (black colour solid line, denoted as 'HF') and their replicating portfolios using four linear models and GAMs during the out-of-sample period from January 2004 to September 2010. Clones are constructed based on four models, the linear models HL6 and SLM14; and the nonlinear models GAML6 and SGAML14 using a rolling window procedure.




DSB
HF
HL6
GAML6
SLM14
SGAML14
Return
0.15
0.10
0.05
0.00
−0.05
−0.10
Jan 04
Jul 04
Jan 05
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Jan 06
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Jan 07
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Jan 08
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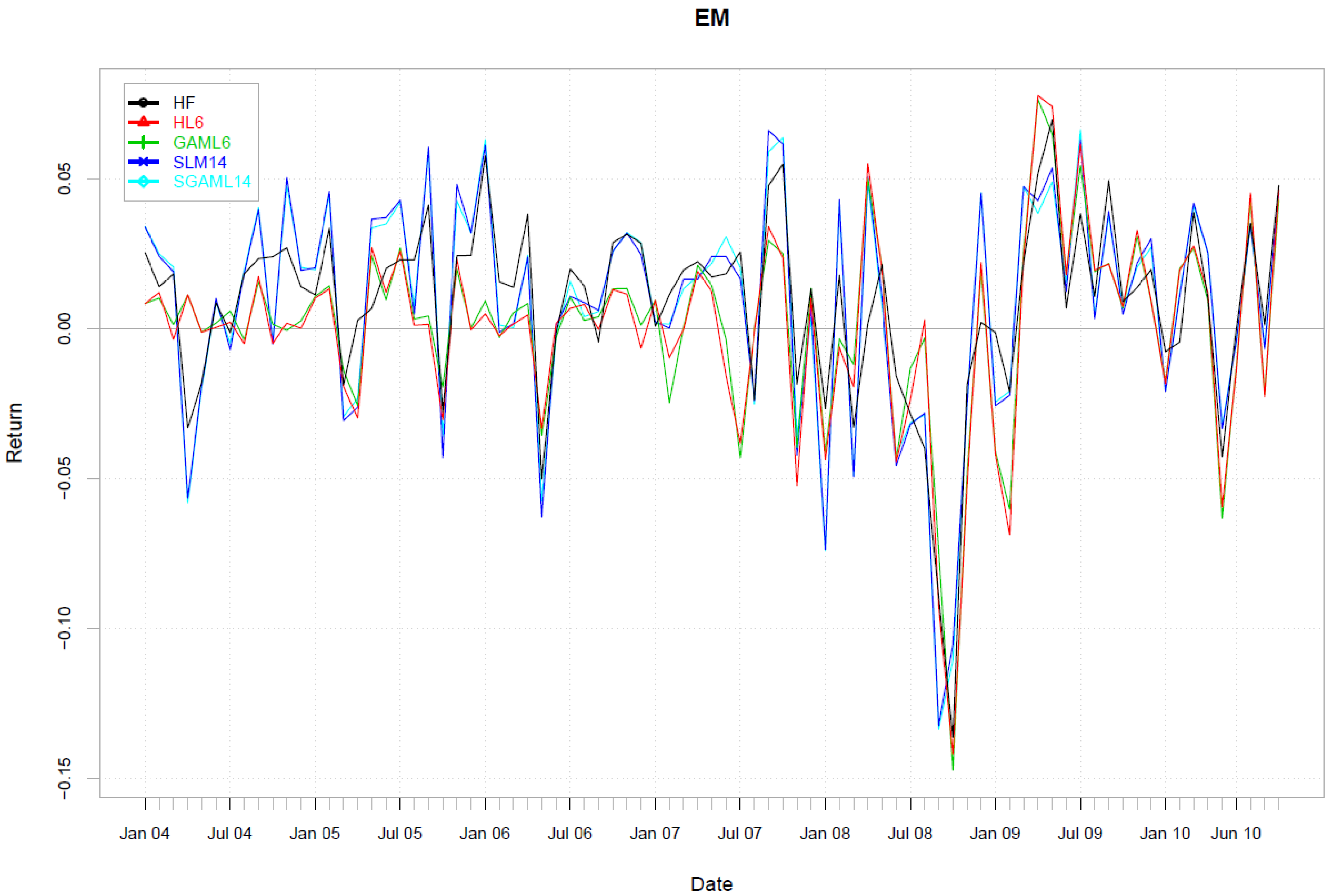
Jan 09
Jul 09
Jan 10
Jun 10
Date


EM
HF
HL6
GAML6
SLM14
SGAML14
Return
0.05
0.00
−0.05
−0.10
−0.15
Jan 04
Jul 04
Jan 05
Jul 05
Jan 06
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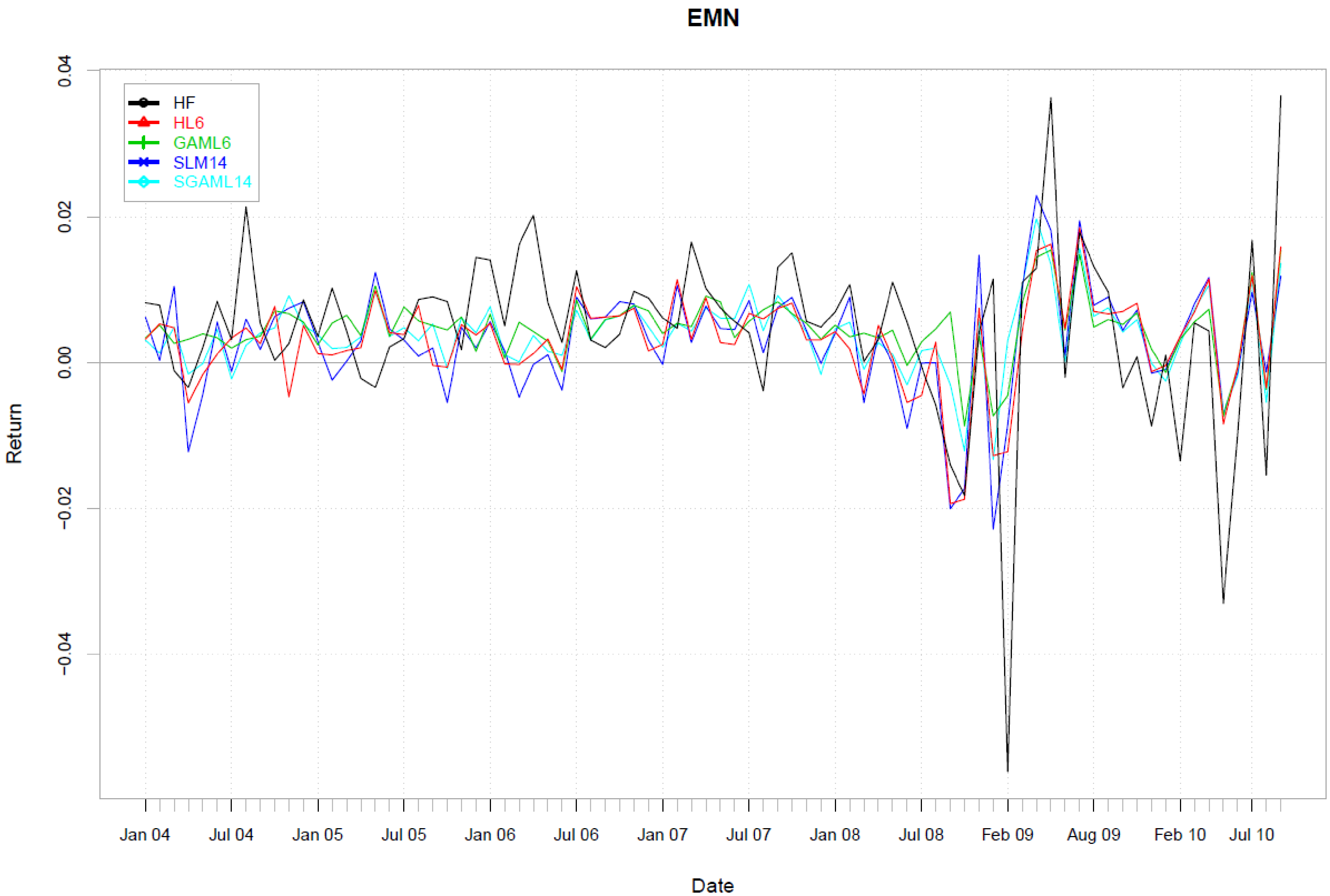
Jan 07
Jul 07
Jan 08
Jul 08
Jan 09
Jul 09
Jan 10
Jun 10
Date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HF
HL6
GAML6
SLM14
SGAML14
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0.02
0.00
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Return
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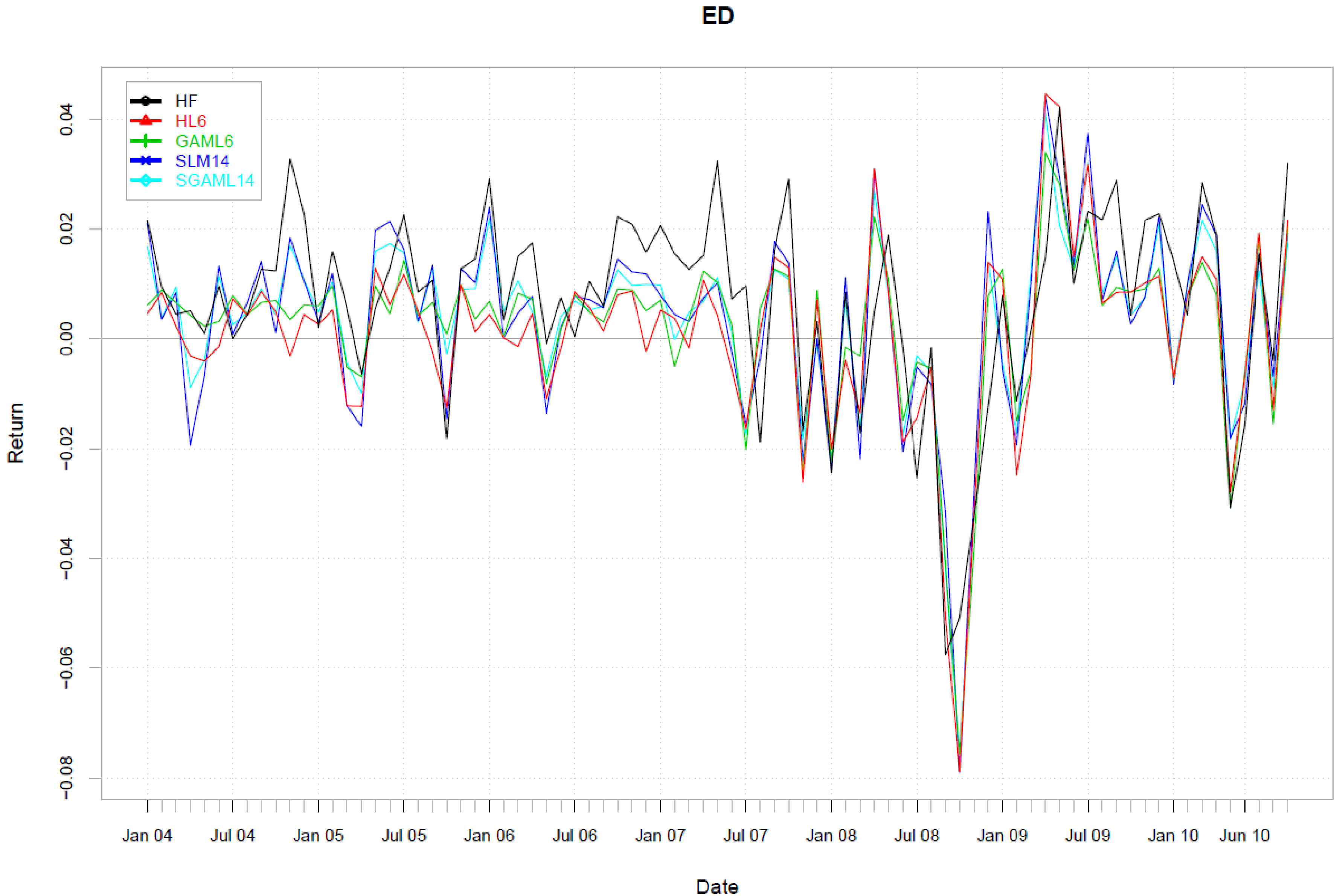
Aug 09
Feb 10
Jul 10
Date



ED
HF
HL6
GAML6
SLM14
SGAML14
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0.02
0.00
−0.02
−0.04
−0.06
−0.08
Return
Jan 04
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Jul 07
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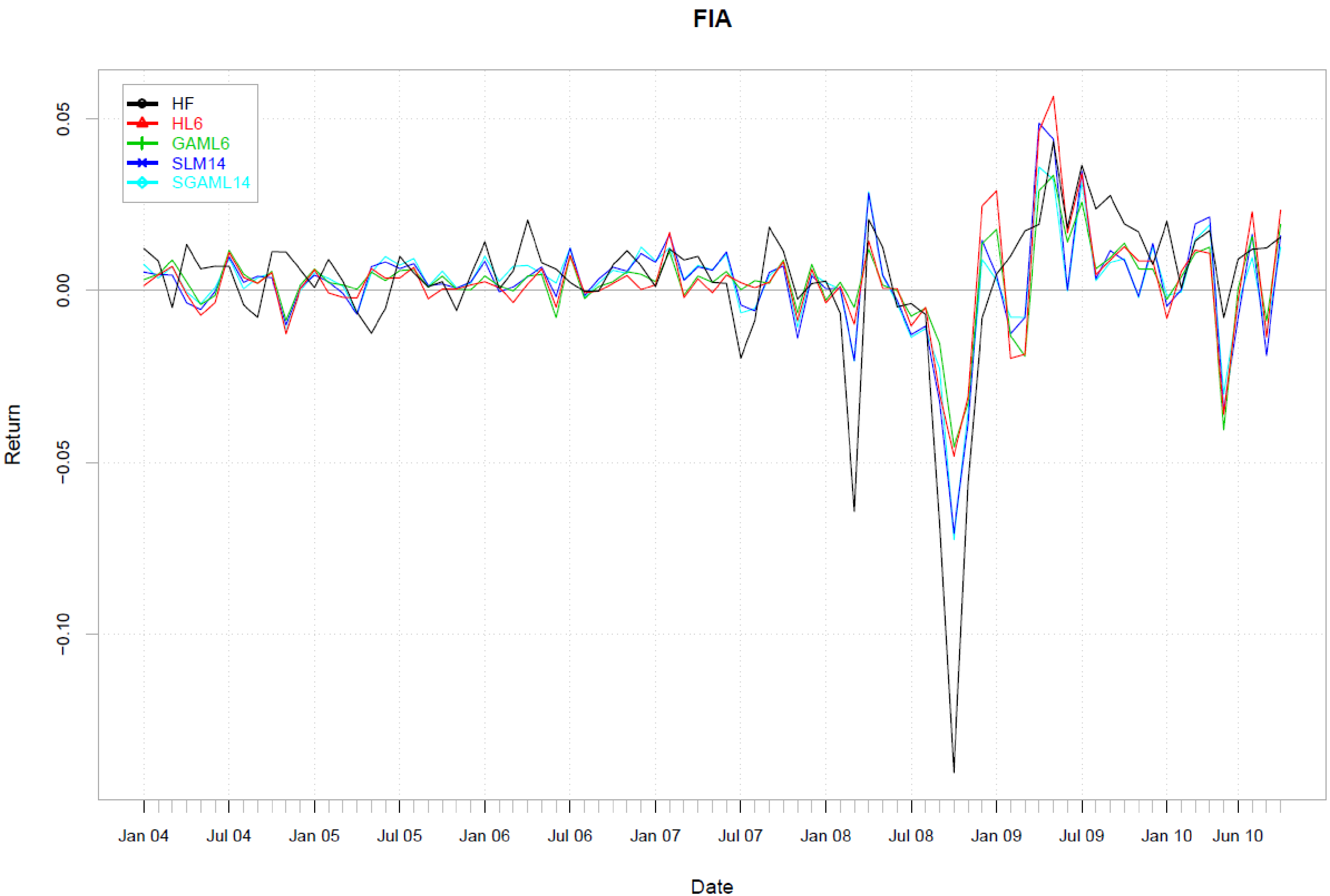
Jul 09
Jan 10
Jun 10
Date



FIA
HF
HL6
GAML6
SLM14
SGAML14
Return
0.05
0.00
−0.05
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Date
Jan 04
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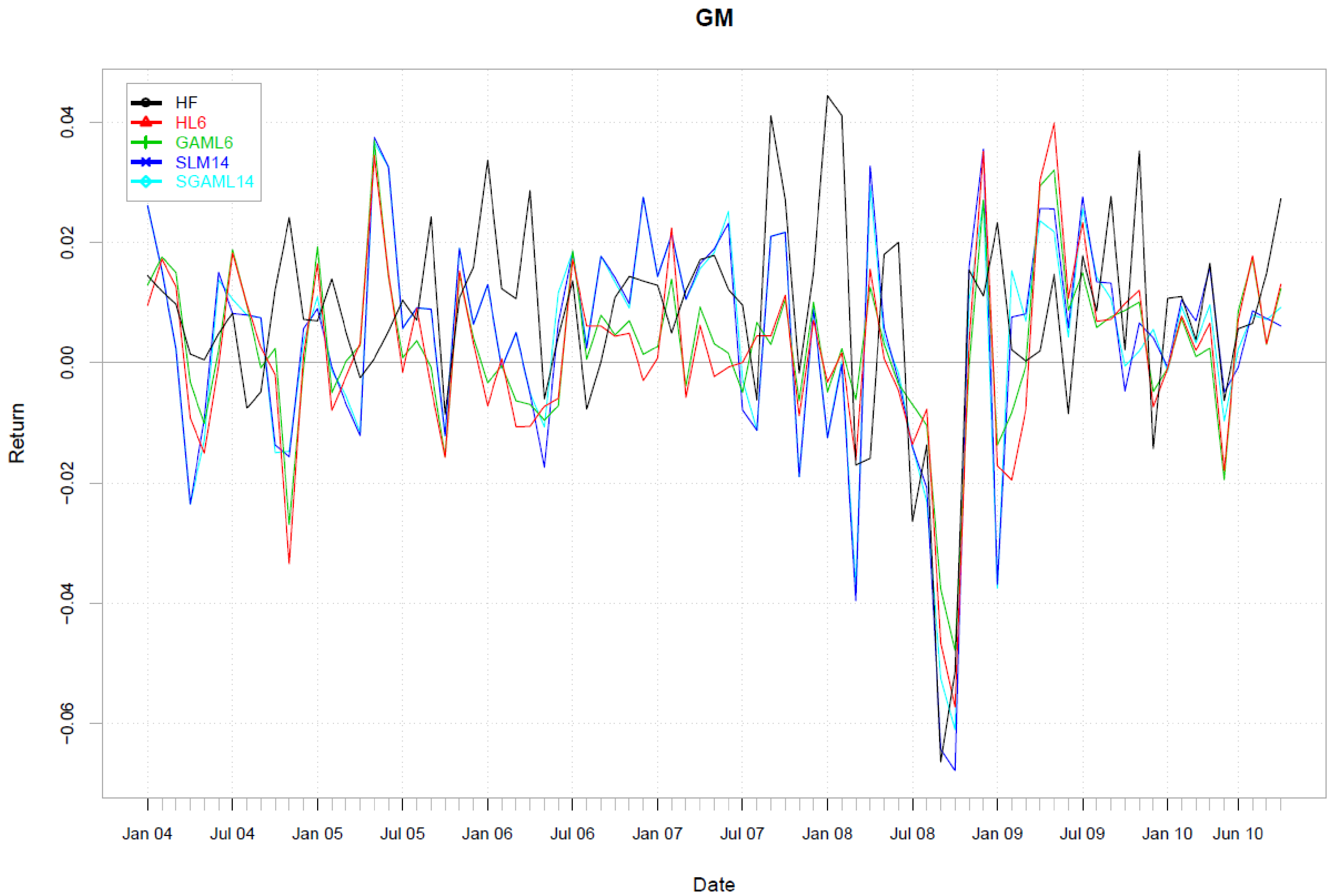
Jun 10


GM
HF
HL6
GAML6
SLM14
SGAML14
Return
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0.02
0.00
−0.02
−0.04
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Jan 04
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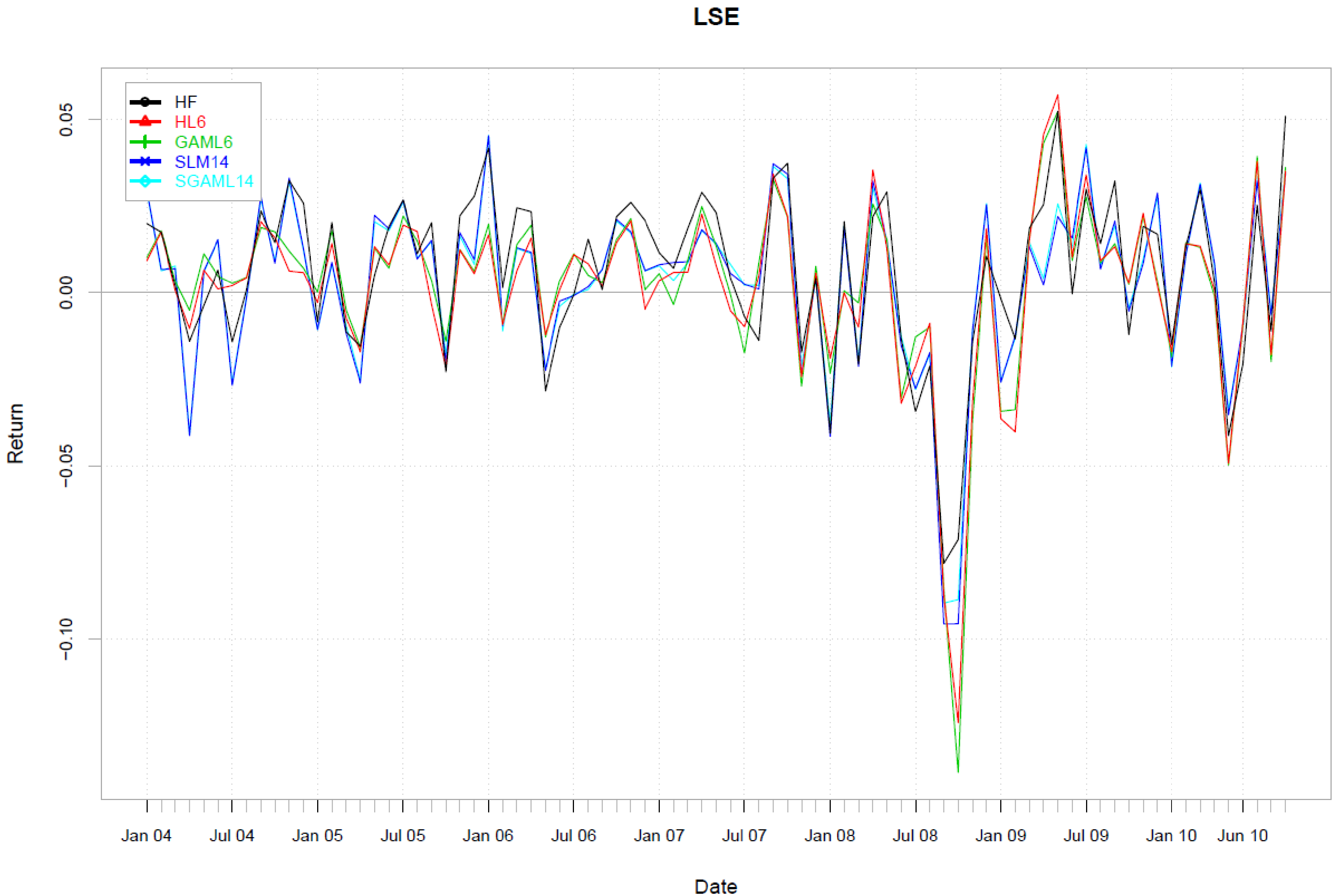
Date



LSE
HF
HL6
GAML6
SLM14
SGAML14
0.05
0.00
−0.05
−0.10
Return
Jan 04
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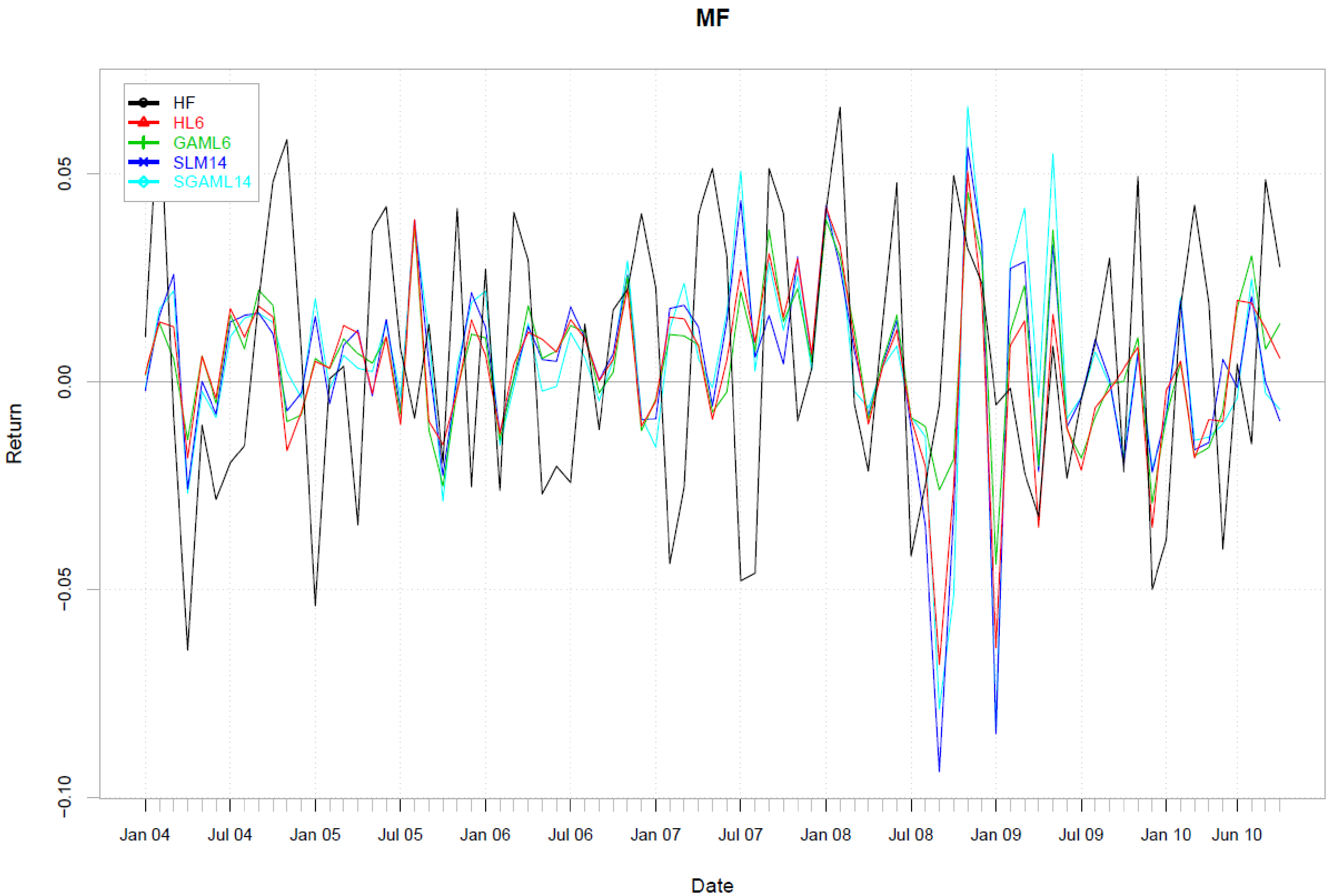
Jan 10
Jun 10
Date


MF
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GAML6
SLM14
SGAML14
Return
0.05
0.00
−0.05
−0.10
Jan 04
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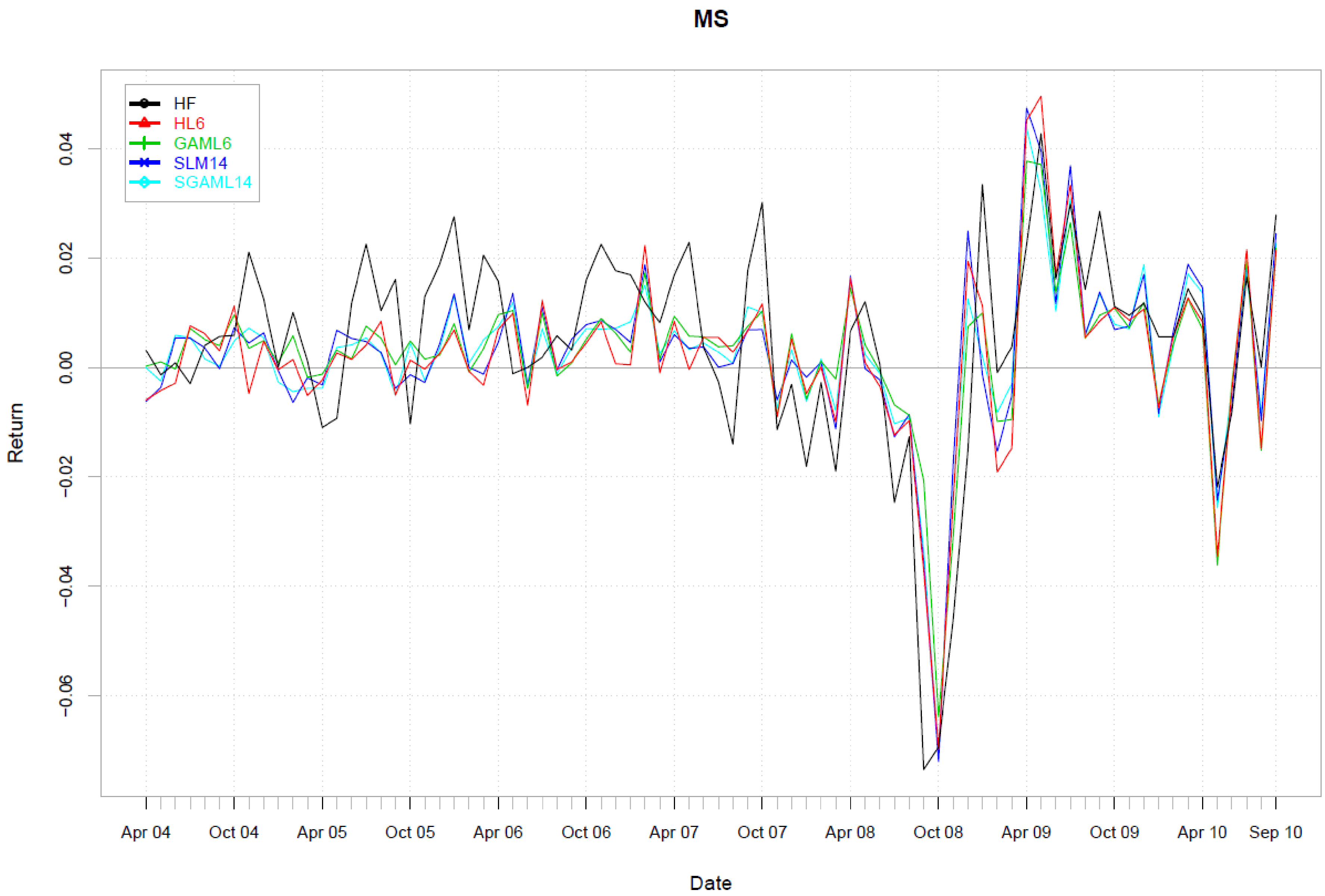
Jun 10
Date


MS
HF
HL6
GAML6
SLM14
SGAML14
Return
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0.02
0.00
−0.02
−0.04
−0.06
Apr 04
Oct 04
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Apr 06
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Apr 07
Oct 07
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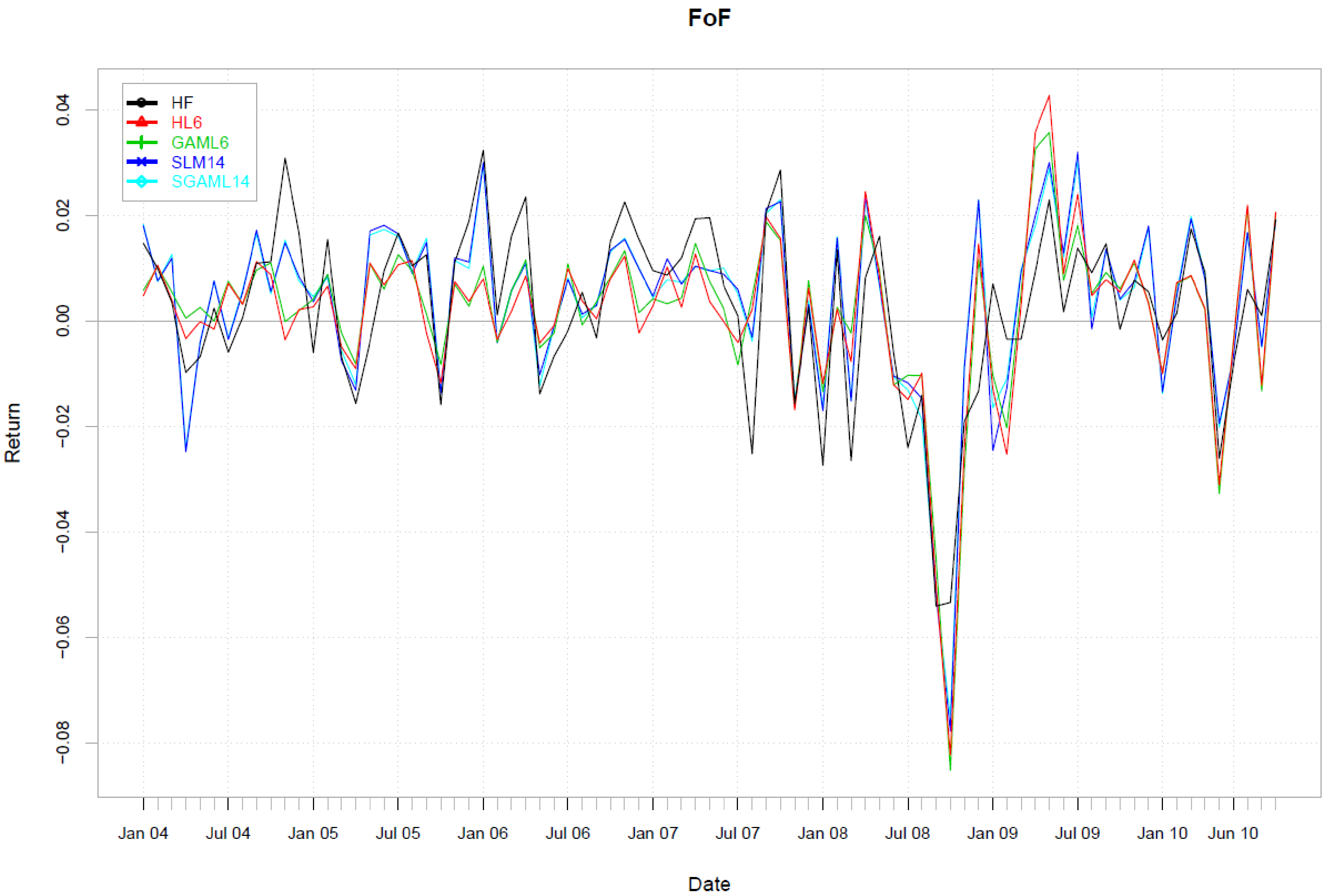
Oct 08
Apr 09
Oct 09
Apr 10
Sep 10
Date


FoF
HF
HL6
GAML6
SLM14
SGAML14
0.04
0.02
0.00
-0.02
-0.04
-0.06
-0.08
Return
Jan 04
Jul 04
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Jan 06
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Date

Finally, Table 8.7 presents the details of the performance analysis of TASS clones relatively to TASS indices. As the table shows nonlinear clones have lower excess Sharpe ratio, modified Sharpe ratio and Sortino ratio than linear clones in seven styles and eight styles out of twelve in case of the 14-factor and the six-factor models respectively. The test for significance of the excess Sharpe ratio for the 14-factor linear and nonlinear clones indicates that the risk-adjusted performance of clones and indices does not significantly differs in eight styles. In terms of the information ratio, the six-factor nonlinear clones outperform linear clones in eleven styles, while the 14-factor clones outperform in six styles. In one third of the styles clones exhibit higher tail risk, in another third – lower tail risk, and comparable tail risk in the remaining one third of the styles.

To summarize, the results are consistent with the earlier findings for HFRI indices. Therefore, it is concluded that the main findings of this chapter are robust to the choice of hedge fund indices and set of risk factors.

Table 8.7 Performance Characteristics of TASS Replicating Portfolios

The table presents the annualized Sharpe ratio; excess Sharpe ratio of clone over TASS index (Δ*Sharpe*) with t-statistic; modified Sharpe ratio (*Mod. Sharpe*), excess modified Sharpe ratio; Sortino ratio; excess Sortino ratio (Δ*Sortino*); annualized information ratio (*Inform. Ratio*); expected shortfall (*ES*); and excess expected shortfall (Δ*ES*). Linear clones are based on models SLM14 and HL6; nonlinear clones are based on models SGAML14 and GAML6. Values of Δ*Sharpe* marked with *, **, and *** are significant at the 10, 5, and 1% levels, respectively.

Style	Model	Sharpe	ΔSharpe	t-stat	Mod. Sharpe	ΔMod. Sharpe	Sortino	ΔSortino	Inform. Ratio	ES	ΔES
CA	Index	0.408			0.219		0.164			-0.112	
	SLM14	0.467	0.059	-0.171	0.298	0.079	0.207	0.043	-0.150	-0.060	0.052
	SGAML14	0.460	0.052	-0.138	0.297	0.078	0.204	0.040	-0.188	-0.054	0.058
	HL6	0.458	0.050	-0.115	0.327	0.108	0.222	0.057	-0.127	-0.041	0.071
	GAML6	0.798	0.390	-1.062	0.558	0.339	0.363	0.199	0.064	-0.042	0.070
DSB	Index	-0.200			-0.122		-0.052			-0.089	
	SLM14	0.222	0.422	-1.577	0.172	0.294	0.144	0.196	0.581	-0.063	0.026
	SGAML14	0.063	0.263	-0.985	0.051	0.173	0.066	0.117	0.373	-0.064	0.025
	HL6	0.209	0.410	-1.382	0.171	0.293	0.142	0.194	0.512	-0.062	0.027
	GAML6	0.140	0.340	-1.148	0.109	0.231	0.103	0.154	0.435	-0.065	0.024
EM	Index	0.892			0.534		0.371			-0.098	
	SLM14	0.722	-0.170	0.683	0.432	-0.102	0.314	-0.057	-0.024	-0.091	0.007
	SGAML14	0.737	-0.155	0.647	0.439	-0.095	0.318	-0.054	-0.010	-0.093	0.005
	HL6	-0.035	-0.927***	2.952	-0.019	-0.553	0.009	-0.362	-1.346	-0.106	-0.008
	GAML6	0.068	-0.824***	2.744	0.037	-0.497	0.045	-0.326	-1.246	-0.110	-0.012
EMN	Index	1.265			0.834		0.538			-0.045	
	SLM14	1.367	0.102	-0.183	0.977	0.143	0.652	0.114	-0.453	-0.018	0.027
	SGAML14	2.525	1.259**	-2.005	2.636	1.802	1.599	1.061	-0.207	-0.010	0.036
	HL6	1.603	0.338	-0.685	1.174	0.340	0.770	0.232	-0.492	-0.016	0.030
	GAML6	3.750	2.485***	-4.362	5.874	5.040	2.770	2.232	0.088	-0.007	0.039
ED	Index	1.350			0.889		0.591			-0.041	
	SLM14	0.731	-0.619*	1.927	0.439	-0.449	0.308	-0.283	-0.933	-0.056	-0.014
	SGAML14	0.779	-0.571*	1.932	0.453	-0.435	0.311	-0.280	-1.045	-0.056	-0.015
	HL6	0.171	-1.179***	3.896	0.095	-0.794	0.075	-0.516	-1.754	-0.061	-0.020
	GAML6	0.484	-0.866***	2.907	0.260	-0.628	0.182	-0.409	-1.462	-0.055	-0.014
FIA	Index	0.351			0.181		0.130			-0.099	
	SLM14	0.431	0.080	-0.236	0.261	0.080	0.183	0.052	-0.087	-0.056	0.044
	SGAML14	0.500	0.149	-0.522	0.284	0.103	0.199	0.068	-0.073	-0.059	0.040
	HL6	0.543	0.192	-0.491	0.401	0.220	0.259	0.129	-0.005	-0.030	0.070
	GAML6	0.687	0.336	-0.862	0.411	0.230	0.280	0.150	0.000	-0.039	0.060
GM	Index	1.596			1.120		0.726			-0.050	
	SLM14	0.765	-0.831**	1.992	0.451	-0.669	0.315	-0.410	-0.706	-0.052	-0.002
	SGAML14	0.826	-0.77*	1.744	0.496	-0.623	0.345	-0.381	-0.710	-0.045	0.006
	HL6	0.378	-1.218**	2.592	0.228	-0.892	0.166	-0.560	-1.197	-0.044	0.007
	GAML6	0.679	-0.917*	1.990	0.436	-0.684	0.305	-0.421	-1.074	-0.036	0.015
LSE	Index	0.831	0***		0.515		0.367			-0.057	
	SLM14	0.426	-0.405**	2.445	0.235	-0.280	0.176	-0.191	-0.894	-0.075	-0.018
	SGAML14	0.474	-0.357**	2.166	0.266	-0.249	0.197	-0.170	-0.853	-0.070	-0.013
	HL6	0.184	-0.646***	2.859	0.097	-0.418	0.082	-0.285	-1.115	-0.096	-0.039
	GAML6	0.259	-0.571**	2.405	0.135	-0.380	0.107	-0.260	-0.941	-0.106	-0.049
MF	Index	0.483			0.320		0.248			-0.057	
	SLM14	0.553	0.070	-0.102	0.319	-0.001	0.232	-0.015	-0.079	-0.076	-0.019
	SGAML14	0.639	0.156	-0.261	0.401	0.081	0.288	0.041	-0.015	-0.068	-0.012
	HL6	0.562	0.080	-0.116	0.338	0.018	0.241	-0.006	-0.136	-0.054	0.003
	GAML6	0.932	0.449	-0.851	0.681	0.361	0.480	0.232	0.004	-0.031	0.026
MS	Index	0.835			0.487		0.338			-0.058	
	SLM14	0.632	-0.204	0.666	0.397	-0.090	0.274	-0.063	-0.502	-0.057	0.001
	SGAML14	0.669	-0.167	0.593	0.402	-0.085	0.275	-0.063	-0.564	-0.059	-0.001
	HL6	0.439	-0.396	1.279	0.271	-0.216	0.190	-0.148	-0.712	-0.054	0.004
	GAML6	0.750	-0.085	0.278	0.449	-0.038	0.303	-0.035	-0.488	-0.053	0.005
FoF	Index	0.540			0.314		0.225			-0.041	
	SLM14	0.739	0.200	-0.750	0.423	0.109	0.296	0.071	0.368	-0.056	-0.015
	SGAML14	0.759	0.220	-0.857	0.436	0.122	0.304	0.079	0.392	-0.054	-0.013
	HL6	0.283	-0.257	0.885	0.153	-0.160	0.114	-0.111	-0.352	-0.066	-0.025
	GAML6	0.383	-0.157	0.525	0.205	-0.109	0.147	-0.079	-0.241	-0.067	-0.026
HFC	Index	1.022			0.625		0.428			-0.050	
	SLM14	0.705	-0.316	1.265	0.403	-0.221	0.285	-0.143	-0.440	-0.063	-0.013
	SGAML14	0.672	-0.350	1.434	0.381	-0.244	0.271	-0.157	-0.543	-0.064	-0.013
	HL6	0.259	-0.763***	2.701	0.144	-0.481	0.109	-0.319	-1.157	-0.070	-0.020
	GAML6	0.358	-0.663**	2.472	0.192	-0.433	0.140	-0.288	-1.101	-0.073	-0.023

8.5 Conclusion

The results of this chapter contribute towards achieving the main goal of the thesis of providing a comprehensive analysis and evaluation of hedge funds' nonlinear risk exposures. While the previous chapters develops nonlinear models and establish significance of nonlinearities in hedge funds' portfolios and individual funds, this chapter investigates the importance of nonlinearities for potential hedge fund investors from a practical perspective, i.e. in the context of hedge fund replication.

To evaluate whether nonlinear effects in hedge funds' risk exposures have economically significant magnitude, it is proposed to construct hedge funds' replicating portfolios using a linear and a nonlinear approach. At the moment synthetic replication of hedge fund strategies is an active area of research which has a great potential in terms of practical applications. Since most of the models used so far for replication are linear, the area provides particularly interesting setting for economic evaluation of nonlinearities.

There are several main findings in the chapter. Firstly, nonlinear clones of non-investable broad hedge fund style indices have higher tracking accuracy (lower tracking error and MAE) than linear clones in most of the styles. The average tracking error across the styles is 14b.p. less for nonlinear clones. In some styles the difference is as high as 38b.p. Due to the lower tracking error average underperformance of nonlinear clones relative to benchmarks measured by the average excess returns is lower by 6b.p p.a. or 29b.p. over the whole period. The results are consistent in sub-periods during and after the recent financial crisis. The improved ability of nonlinear clones to mimic hedge fund returns lead to a smaller difference in performance ratios between clones and benchmarks. It is evidenced by lower average excess Sharpe ratio, excess modified Sharpe ratio and excess Sortino ratio. Also, nonlinear clones would be more attractive for investors in terms of higher average information ratio, and better representation of the true negative tail risk of hedge fund strategies. The latter point in not surprising given that the tail risk of hedge funds is driven partly by extreme nonlinear risk exposures, such as those of short deep out-of-the-money put option positions.

The second major finding is related to the analysis of tracking accuracy of hedge fund clones and investable hedge fund indices. HFRX investable indices provided by HFR are comprised of a small subset of funds open to investors and are designed to mimic the performance of their non-investable counterparts. The overwhelming evidence provided in this chapter suggests that synthetic hedge fund clones, both linear and nonlinear, have much better ability to track the performance of the hedge fund strategies than investable hedge fund indices. The annual tracking error of the clones is 70-80b.p. p.a. lower. Moreover, it is found that higher tracking error of investable indices is driven by lower absolute and risk-adjusted performance. Their average cumulated excess performance reaches -24.59% against -4.97% for nonlinear clones over the period January 2008 – February 2014. Poor performance is also exacerbated by much higher left tail risk. These findings cannot be underestimated, because most of the hedge funds comprising a theoretical hedge fund index, such as TASS or HFRI index are closed to public investors. Therefore, for a hedge fund investor who wants to get access to hedge fund alpha and/or beta, the real alternative to hedge fund clones is an investable hedge fund index, e.g. HFRX, and not a theoretical index used widely in academic research.

To summarize, the findings of this chapter contribute to the hedge fund literature as they provide evidence that:

(i) hedge funds’ indices have common factor exposures which can be captured and exploited to construct passive replicating strategies;

(ii) by replicating hedge fund strategies synthetically it is possible to construct benchmarks which better represent the performance of the hedge fund universe than investable indices do, even though funds comprising investable indices are usually chosen to maximize the representativeness and minimize tracking error;

(iii) hedge funds at least in certain styles have nonlinear risk exposures; nonlinearities are not only statistically significant as confirmed in previous chapters, but are also of economically significant magnitude, because nonlinear clones have lower tracking error than linear clones;

(iv) the approach used to capture nonlinear risk exposures of hedge funds matters; while Amenc et al. (2010, p. 203) concludes that “conditional and nonlinear models, which are less parsimonious than their linear counterparts, do not necessarily lead to improved out-of-sample replication” the results of this chapter show that a nonparametric approach based on a GAM does lead to the improvement in the out-of-sample tracking error.

Chapter 9 Conclusions

The issue of nonlinearities is crucial for understanding the many aspects of hedge fund performance. The standard decomposition of hedge fund returns into alpha and beta components (i.e. the abnormal return due to superior manager skill and the systematic risk premium) adopted in the literature relies on the assumption that the exposure to risk factors is linear. Although some nonlinear patterns in hedge funds' risk exposures have been documented in the extant literature, the existence of nonlinearities has not been thoroughly tested. This study fills this gap in the literature.

The major contribution to knowledge provided by this thesis is empirical proof that hedge funds have nonlinear exposures to various systematic risk factors. It is however also found that nonlinearities per se, arising due to complex dynamic hedge fund trading strategies, do not provide a signal of superior fund manager skill to generate positive returns. This is an important finding for hedge fund stakeholders and investors.

In the following sections we discuss in more detail the contributions related to the three research areas set out in the introduction. Sections 9.1 and 9.2 summarize findings pertaining to modeling and analysis of nonlinearities at portfolio and fund level respectively; and Section 9.3 provides comments on results related to linear and nonlinear hedge fund replication.

9.1 Modeling and Assessing Nonlinearities in Hedge Fund Indices

Three contributions have been made to the assessment and modeling of nonlinearities in hedge fund indices. In the first contribution, the thesis provides strong statistical evidence of nonlinearities in the returns of hedge fund portfolios. Prior research into hedge fund returns has been mostly confined to in-sample analysis; the results of the few studies that have carried out the out-of-sample testing until now however, have been inconclusive in determining the presence of nonlinear patterns in hedge fund portfolio returns (Amenc et al., 2010). Our research contributes to the literature by applying an extensive set of out-of-sample tests to verify the existence of nonlinear risk exposures in hedge fund portfolio returns. The implication of this finding is that nonlinearities must be accommodated when analysing and modeling hedge fund risks and returns. To not recognize the nonlinearities present may result in an underestimation of the systematic risk component in hedge fund returns and left tail risk, especially given that nonlinearities are particularly pronounced at the boundaries of return distributions.

In the second contribution, several nonparametric models are proposed in order to capture and examine the presence of nonlinearities. These nonparametric models are more flexible than strictly linear models, allowing a model's functional form to be determined via the data, rather than through an *a priori* setting. Removing restrictions on a model's functional form is useful for uncovering complex patterns within the hedge fund data. Such nonparametric pricing kernels have been successfully applied in the asset pricing literature (Aït - Sahalia & Lo, 1998; Bansal, Hsieh, & Viswanathan, 1993; Bansal & Viswanathan, 1993; Dittmar, 2002), but in the context of hedge fund research, they have not previously been thoroughly analysed. The nonparametric models examined in this study include: a generalized additive model (GAM) using loess and spline base smoothers, a robust version of a GAM using component-wise gradient boosting and a piecewise linear regression model based on a first order multivariate adaptive regression spline (MARS). GAMs were introduced to the modeling of hedge fund returns through the work of Tupitsyn and Lajbcygier (2013) and Lahiri et al. (2013), where the utility of GAMs in exploring the asymmetric patterns present in hedge fund risk exposures was first demonstrated.

The thesis results demonstrate that the nonparametric model based on a GAM using loess smoothers, has a lower tracking error when compared with the seven-factor Fung and Hsieh (2004b) model, the six-factor Hasanhodzic and Lo (2007) model, or the 14-factor stepwise linear regression model using factors identified from earlier studies. The seven-factor Fung and Hsieh (2004b) model is widely accepted in the literature, being judged sufficiently flexible to accommodate hedge fund nonlinearities. As found in the thesis however, the seven-factor model does not outperform, in either in-sample and out-of-sample tests, a linear multi-factor model such as the six-factor model of Hasanhodzic and Lo (2007). The three nonlinear trend following factors in the seven-factor model have been designed specifically to capture nonlinear strategies of trend following CTA funds. As the analysis shows, these factors do not provide any additional explanatory power to the model in any of the styles other than the CTAs. Other models therefore are required to accommodate nonlinearities in arbitrage related and multi-factor styles. The GAM in contrast outperforms the linear model in most of the styles.

In the third contribution, investigations at the hedge fund portfolio level reveal that nonlinear risk exposures are more common in arbitrage strategies than in directional strategies. Consistent with other studies (Agarwal & Naik, 2004; Mitchell & Pulvino, 2001) it is found that arbitrage related styles exhibit nonlinear patterns resembling payoffs of short put option positions. Funds from these styles earn small profits during stable market environments and suffer significant losses during financial distress situations, when market volatility increases and yield spreads rise. In contrast, directional strategies mostly have linear risk exposures in their focus markets. For instance, the Long-Short equity style is linearly exposed to equity risk and the size spread. This result is consistent with the findings of Fung and Hsieh (2004a).

9.2 Assessing Nonlinearities in Individual Funds

GAMs and linear models are applied to examine nonlinearities at the individual fund level. All the funds are classified into three groups based on the form of their risk exposures: the funds with linear only risk exposures, the fund with any nonlinear risk exposure, and the funds with insignificant linear and nonlinear risk exposures. To address the potential concern of multiple hypotheses testing bias critical values for significance tests are derived using simulation techniques. The simulation analysis is important, because it helps to guard against making spurious conclusions about the nonlinearities. It shows that R^2 of multi-factor models applied to individual funds as high as 30% can be obtained purely by chance. Thus, appropriate thresholds are determined and used for classification of risk exposures of hedge funds.

The analysis of nonlinearities shows that around one-fifth of funds have nonlinear risk exposures, two-thirds of funds exhibit only linear exposures and the rest of the funds demonstrate market-neutral risk profile. These results reconcile the findings of Bollen (2013) and Diez de los Rios and Garcia (2011). Bollen (2013) studies funds with linear systematic risk exposures and risk-neutral funds; the author reports a very close estimate of the number of linear funds to the figure estimated in this thesis, i.e. around one-third. Diez de los Rios and Garcia (2011) focus on nonlinear funds. The authors' estimate of the number of nonlinear funds also closely matches to that obtained in this research, i.e. around one-fifth. Accordingly, the classification scheme proposed in the thesis which encompasses three types of funds, i.e. linear, nonlinear, and risk-neutral, is more complete, and at the same time is consistent with previous studies. The finding that funds within styles have different forms of exposures suggests that fund managers execute different types of investment strategies with different risk return profiles; hence the analysis of nonlinearities in individual funds is essential. Similar to the results at the portfolio level the analysis suggests that there are more nonlinear funds among arbitrage related styles compared with directional styles. Nevertheless, even in arbitrage styles more than half of the funds do not exhibit significant nonlinearities.

Furthermore, the three groups of funds with linear, nonlinear and insignificant risk exposures demonstrate different performance characteristics. Overall, the nonlinear funds have lower raw returns, risk-adjusted returns and higher negative tail risk than linear funds and risk-neutral funds. This is an important observation as it points out that in aggregate funds employing complex trading strategies with nonlinear payoffs do not generate additional value to investors relatively to a portfolio of funds following more simple strategies with linear payoffs. In other words, nonlinearities per se do not signal skill among fund managers. In addition, there is evidence suggesting that managers of nonlinear funds change more frequently their trading approach and the form of fund's risk exposures, than do managers of linear funds: 55-75% of nonlinear funds eventually convert to linear funds, while 70-85% of linear funds retain the linear risk exposure profile. This behaviour is not surprising, because relative performance is an important factor for AUM growth; thus, managers of nonlinear funds take action and adjust risk-return profile of their funds in order to fight for AUM and deviate less from their more successful linear peers.

9.3 Hedge Fund Replication and Nonlinear Risk

Lack of evidence of skill among managers of funds with nonlinearities naturally leads to the third issue examined in the thesis, i.e. a passive hedge fund replication. If hedge fund returns are driven mostly by the risk premium, i.e. linear and nonlinear risk exposures, clones of the hedge fund beta could make a cost efficient alternative to direct hedge fund investing.

To this end the two best linear and nonparametric models (i.e. the models with the lowest out-of-sample tracking error) have been applied to investigate the potential performance of passive linear and nonlinear hedge fund clones. The benchmarks used for the clones are the two types of HFR style indices: HFRI non-investable broad hedge fund indices, and HFRX investable indices. Most of the studies on hedge fund replication focus on linear clones of non-investable indices (Giamouridis & Paterlini, 2010; Hasanhodzic & Lo, 2007) and do not consider potential differences existing between the two types of indices. The replication analysis suggests that nonlinear clones of non-investable indices have higher tracking accuracy (lower tracking error and MAE) than linear clones in most of the styles. As a result, nonlinear clones better match performance characteristics of HFRI indices than linear clones. The results are consistent across two sub-periods during and after the recent financial crisis. The robustness tests using TASS indices and six-factor models also validate the results. Thus, these findings confirm that nonlinearities in hedge funds are genuine.

Also, another interesting and unexpected finding that has emerged from the replication analysis is related to the performance of investable indices. The overwhelming statistical evidence suggests that synthetic hedge fund clones, both linear and nonlinear, have much better ability to track the performance of hedge fund strategies than investable hedge fund indices. Despite the claim of the provider that investable indices are designed to be representative of the performance of broad hedge fund universe and hedge fund strategies, they dramatically underperform non-investable indices, on average by -4.7% p.a. Jeremy Duffield, a former CEO of Vanguard Australia, has attributed this effect to the "Groucho Marx" effect: funds in investable indices have capacity because no one is interested to invest in them. An important practical implication of this result is that investable indices can hardly be recommended to investors who want to get a broad exposure to hedge funds. Rather, hedge fund clones can provide much better alternative. Statistical tests show that neither raw nor risk-adjusted performance of most of the linear and nonlinear clones of non-investable HFRI indices differs from their benchmarks. Thus, this study provides support to the concept of hedge fund replication.

9.4 Limitations

This section considers the limitations of the nonparametric methodology applied for the analysis of hedge funds' nonlinear risk exposures. The first limitation lies with the constraint imposed on the intercept term in a GAM. As explained in Section 5.3.2 the intercept term is calculated as the mean value of hedge fund returns (i.e. $\alpha_i = E(R_{i,t})$). This constraint is necessary to ensure the unicity of the GAM: without it smoother functions would be defined only up to an additive constant. The implication of the constraint is that a GAM does not allow the standard interpretation of the alpha term as an abnormal return above the systematic risk premium. Therefore, a GAM in this thesis is used as a tool for exploration of nonlinearities and not as a hedge fund pricing model. Nevertheless, there are ways to overcome this issue, such as one proposed in Section 5.3.2. Specifically, a GAM can be used in combination with the linear model; it is fitted to the residuals of the linear model rather than to hedge fund returns. In this way a GAM helps to identify nonlinearities not capture by the linear model.

Another limitation is related to the sample size: the dataset with TASS indices spans from 1994 to 2010. At the time this research started in 2011 the author had a one-off access to the TASS database which was updated until September 2010. Accordingly, the out-of-sample period analysed in this study was limited to January 2005 – September 2010. Given that nonlinearities are most pronounced at the tails of return distributions where the number of observations is usually small it would be important to check the results on a larger dataset. It is expected that a larger dataset would provide a stronger results about the statistical and economic significance of nonlinearities. Currently, TASS indices are published on Credit Suisse web-site. Therefore, portfolio level analysis can be extended to include the recent period. However, the data on individual funds are not publicly available and require subscription to the TASS database.

Finally, a nonlinear replication approach using a GAM does not represent a true investable trading strategy; rather it provides a theoretical test of potential performance of the clone conditional on the realized values of the factors in the out-of-sample period. Due to the nonlinear shape of risk exposure functions, risk exposures are not time invariant in nonlinear models. Therefore, predictions of hedge fund returns require forecasts of factor returns. This issue which is not specific to the GAM approach but affects other nonlinear models such as the threshold linear regression model of Giannikis and Vrontos (2011) has not been highlighted earlier in the literature. Therefore, the results on nonlinear replication should be viewed as another form of confirmation of the importance of nonlinearities.

9.5 Further Work

The limitations discussed above suggest potential avenues for further research. First of all, the knowledge about nonlinearities provided by GAMs could be used to develop a better hedge fund pricing model. As the analysis suggests, there is strong empirical evidence of nonlinearities in hedge fund styles and in particular in arbitrage related categories; however, existing models including the seven-factor Fund and Hsieh (2004) model mostly fail to account for them. Thus, nonparametric techniques such as GAMs could be used as benchmarks for new theoretical models of hedge fund nonlinearities. Developing an adequate hedge fund pricing model arguably is the most important outstanding problem in hedge fund research.

Another area of research which has strong potential for further discoveries is related to the results and observations made on hedge fund replication and indexation. It has been found that investable indices substantially underperform hedge fund benchmarks. The understanding of exact reasons of this phenomenon would make a step forward towards the creation of better hedge fund benchmarks. Currently non-investable indices are used as benchmarks of broad performance of hedge fund styles. However, if most of the constituent funds are not investable, should investors rely on them when comparing hedge fund performance with other asset classes? Furthermore, since existing investable indices lack representativeness of the hedge fund universe, what can be done to improve them?

Also, since hedge fund clones have demonstrated good relative performance and tracking accuracy, it would be useful to conduct a thorough examination of existing commercial hedge fund replication products. Although a number of products are available in the market today, they have not gained much popularity yet and have not been properly analysed. Due to the increasing long-term institutional allocations to alternative investments and hedge funds in particular, further examination of the topic of hedge fund indexation would be timely and valuable for practitioners.

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Appendix I: TASS Hedge Fund Styles

The following list of category descriptions is taken from Credit Suisse/TASS documentation[126]; it defines the criteria used by TASS in assigning funds in their database to one of 11 categories:

Convertible Arbitrage (CA)

This strategy is identified by hedge investing in the convertible securities of a company. A typical investment is to be long the convertible bond and short the common stock of the same company. 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.

Dedicated Short Bias (DSB)

Dedicated short sellers were once a robust category of hedge funds before the long bull market rendered the strategy difficult to implement. A new category, short biased, has emerged. The strategy is to maintain net short as opposed to pure short exposure. Short biased managers take short positions in mostly equities and derivatives. The short bias of a manager's portfolio must be constantly greater than zero to be classified in this category.

Emerging Markets (EM)

This strategy involves equity or fixed income investing in emerging markets around the world. Because many emerging markets do not allow short selling, nor offer viable futures

[126] http://www.hedgeindex.com/

or other derivative products with which to hedge, emerging market investing often employs a long-only strategy.

Equity Market Neutral (EMN)

This investment strategy is designed to exploit equity market inefficiencies and usually involves being simultaneously long and short matched equity portfolios of the same size within a country. Market neutral portfolios are designed to be either beta or currency neutral, or both. Well-designed portfolios typically control for industry, sector, market capitalization, and other exposures. Leverage is often applied to enhance returns.

Event Driven (ED)

This strategy is defined as "special situations" investing designed to capture price movement generated by a significant pending corporate event such as a merger, corporate restructuring, liquidation, bankruptcy, or reorganization. There are three popular sub-categories in event-driven strategies: risk (merger) arbitrage, distressed/high yield securities, and Regulation D.

Fixed Income Arbitrage (FIA)

The fixed income arbitrageur aims to profit from price anomalies between related interest rate securities. Most managers trade globally with a goal of generating steady returns with low volatility. This category includes interest rate swap arbitrage, US and non-US government bond arbitrage, forward yield curve arbitrage, and mortgage-backed securities arbitrage. The mortgage-backed market is primarily US-based, over-the-counter, and particularly complex.

Global Macro (GM)

Global macro managers carry long and short positions in any of the world's major capital or derivative markets. These positions reflect their views on overall market direction as influenced by major economic trends and/or events. The portfolios of these funds can include stocks, bonds, currencies, and commodities in the form of cash or derivatives instruments. Most funds invest globally in both developed and emerging markets.

Long-Short Equity (LSE)

This directional strategy involves equity-oriented investing on both the long and short sides of the market. The objective is not to be market neutral. Managers have the ability to shift from value to growth, from small to medium to large capitalization stocks, and from a net long position to a net short position. Managers may use futures and options to hedge. The focus may be regional, such as long/short US or European equity, or sector specific, such as long and short technology or healthcare stocks. Long/Short equity funds tend to build and hold portfolios that are substantially more concentrated than those of traditional stock funds.

Managed Futures (MF)

This strategy invests in listed financial and commodity futures markets and currency markets around the world. The managers are usually referred to as Commodity Trading Advisors, or CTAs. Trading disciplines are generally systematic or discretionary. Systematic traders tend to use price and market specific information (often technical) to make trading decisions, while discretionary managers use a judgmental approach.

Multi-Strategy (MS)

The funds in this category are characterized by their ability to dynamically allocate capital among strategies falling within several traditional hedge-fund disciplines. The use of many strategies, and the ability to reallocate capital between them in response to market opportunities, means that such funds are not easily assigned to any traditional category. The Multi-Strategy category also includes funds employing unique strategies that do not fall under any of the other descriptions.

Fund of Funds

A “multi-manager” fund will employ the services of two or more trading advisors or Hedge Funds who will be allocated cash by the trading manager to trade on behalf of the fund.

Appendix II: HFR Hedge Fund Styles and Composite Indices

This appendix contains the description of HFR styles (HFR, 2014), as well as description of HFRI and HFRX composite hedge funds indices.

Primary Strategy Descriptions:

Equity Hedge (EH)

Equity Hedge strategies maintain positions both long and short in primarily equity and equity derivative securities. A wide variety of investment processes can be employed to arrive at an investment decision, including both quantitative and fundamental techniques; strategies can be broadly diversified or narrowly focused on specific sectors and can range broadly in terms of levels of net exposure, leverage employed, holding period, concentrations of market capitalizations and valuation ranges of typical portfolios. Equity Hedge managers would typically maintain at least 50%, and may in some cases be substantially entirely invested in equities, both long and short.

Event-Driven (ED)

Investment managers who maintain positions in securities of companies currently or prospectively involved in corporate transactions of a wide variety, including but not limited to: mergers, restructurings, financial distress, tender offers, shareholder buybacks, debt exchanges, security issuance or other capital structure adjustments. Security types can range from most senior in the capital structure to most junior or subordinated, and frequently involve additional derivative securities. ED exposure contains a combination of sensitivities to equity markets, credit markets and idiosyncratic, company specific developments. Investment theses are typically predicated on fundamental characteristics (as opposed to quantitative), with the realization of the thesis predicated on a specific development exogenous to the existing capital structure.

Macro (M)

Investment managers which execute a broad range of strategies in which the investment process is predicated on movements in underlying economic variables and the impact these have on equity, fixed income, currency and commodity markets. Managers employ a variety of techniques, both discretionary and systematic analysis, combinations of top down and bottom up theses, quantitative and fundamental approaches and long and short term holding periods. Although some strategies employ relative value techniques, Macro strategies are distinct from relative value strategies in that the primary investment thesis is predicated on future movements in the underlying instruments, rather than realization of a valuation discrepancy between securities. In a similar way, while both Macro and equity hedge managers may hold equity securities, the overriding investment thesis is predicated on the impact movements in underlying macroeconomic variables may have on security prices, as opposes to EH, in which the fundamental characteristics on the company are the most significant and integral to investment thesis.

Relative Value (RV)

Investment managers who maintain positions in which the investment thesis is predicated on realization of a valuation discrepancy in the relationship between multiple securities.

Managers employ a variety of fundamental and quantitative techniques to establish investment theses, and security types range broadly across equity, fixed income, derivative or other security types. Relative Value Arbitrage position may be involved in corporate transactions also, but as opposed to event driven exposures, the investment thesis is predicated on realization of a pricing discrepancy between related securities, as opposed to the outcome of the corporate transaction.

Emerging Markets (EM)

Emerging Markets funds invest, primarily long, in securities of companies or the sovereign debt of developing or 'emerging' countries. Emerging Markets regions include Africa, Asia ex-Japan, Latin America, the Middle East and Russia/Eastern Europe. Emerging Markets - Global funds will shift their weightings among these regions according to market conditions and manager perspectives.

Sub-Strategy Descriptions:

EH: Equity Market Neutral (EMN)

Equity market neutral strategies employ sophisticated quantitative techniques of analysing price data to ascertain information about future price movement and relationships between securities, select securities for purchase and sale. These can include both Factor-based and Statistical Arbitrage/Trading strategies. Factor-based investment strategies include strategies in which the investment thesis is predicated on the systematic analysis of common relationships between securities. In many but not all cases, portfolios are constructed to be neutral to one or multiple variables, such as broader equity markets in dollar or beta terms, and leverage is frequently employed to enhance the return profile of the positions identified. Statistical Arbitrage/Trading strategies consist of strategies in which the investment thesis is predicated on exploiting pricing anomalies which may occur as a function of expected mean reversion inherent in security prices; high frequency techniques may be employed and trading strategies may also be employed on the basis on technical analysis or opportunistically to exploit new information the investment manager believes has not been fully, completely or accurately discounted into current security prices. Equity Market Neutral Strategies typically maintain characteristic net equity market exposure no greater than 10% long or short.

EH: Quantitative Directional

Quantitative directional strategies employ sophisticated quantitative analysis of price, other technical and fundamental data to ascertain relationships among securities and to select securities for purchase and sale. These can include both Factor-based and Statistical Arbitrage/Trading strategies. Factor-based investment strategies include strategies in which the investment thesis is predicated on the systematic analysis of common relationships between securities. Statistical Arbitrage/Trading strategies consist of strategies in which the investment thesis is predicated on exploiting pricing anomalies which may occur as a function of expected mean reversion inherent in security prices; high frequency techniques may be employed and trading strategies may also be employed on the basis on technical analysis or opportunistically to exploit new information the investment manager believes has not been fully, completely or accurately discounted into current security prices. Quantitative Directional Strategies typically maintain varying levels of net long or short equity market exposure over various market cycles.

EH: Short-Biased

Short-Biased strategies employ analytical techniques in which the investment thesis is predicated on assessment of the valuation characteristics on the underlying companies with the goal of identifying overvalued companies. Short Biased strategies may vary the investment level or the level of short exposure over market cycles, but the primary distinguishing characteristic is that the manager maintains consistent short exposure and expects to outperform traditional equity managers in declining equity markets. Investment theses may be fundamental or technical and nature and manager has a particular focus, above that of a market generalist, on identification of overvalued companies and would expect to maintain a net short equity position over various market cycles.

ED: Distressed/Restructuring

Distressed/Restructuring strategies which employ an investment process focused on corporate fixed income instruments, primarily on corporate credit instruments of companies trading at significant discounts to their value at issuance or obliged (par value) at maturity as a result of either formal bankruptcy proceeding or financial market perception of near term proceedings. Managers are typically actively involved with the management of these companies, frequently involved on creditors' committees in negotiating the exchange of securities for alternative obligations, either swaps of debt, equity or hybrid securities. Managers employ fundamental credit processes focused on valuation and asset coverage of securities of distressed firms; in most cases portfolio exposures are concentrated in instruments which are publicly traded, in some cases actively and in others under reduced liquidity but in general for which a reasonable public market exists. In contrast to Special Situations, Distressed Strategies employ primarily debt (greater than 60%) but also may maintain related equity exposure.

ED: Merger Arbitrage

Merger arbitrage strategies which employ an investment process primarily focused on opportunities in equity and equity related instruments of companies which are currently engaged in a corporate transaction. Merger Arbitrage involves primarily announced transactions, typically with limited or no exposure to situations which pre-, post-date or situations in which no formal announcement is expected to occur. Opportunities are frequently presented in cross border, collared and international transactions which incorporate multiple geographic regulatory institutions, with typically involve minimal exposure to corporate credits. Merger arbitrage strategies typically have over 75% of positions in announced transactions over a given market cycle.

Macro: Systematic Diversified

Systematic diversified strategies have investment processes typically as function of mathematical, algorithmic and technical models, with little or no influence of individuals over the portfolio positioning. Strategies which employ an investment process designed to identify opportunities in markets exhibiting trending or momentum characteristics across individual instruments or asset classes. Strategies typically employ quantitative process which focus on statistically robust or technical patterns in the return series of the asset, and typically focus on highly liquid instruments and maintain shorter holding periods than either discretionary or mean reverting strategies. Although some strategies seek to employ counter trend models, strategies benefit most from an environment characterized by persistent, discernible trending behaviour. Systematic Diversified strategies typically would expect to have no greater than 35% of portfolio in either dedicated currency or commodity exposures over a given market cycle.

RV: Fixed Income-Convertible Arbitrage

Convertible arbitrage includes strategies in which the investment thesis is predicated on realization of a spread between related instruments in which one or multiple components of the spread is a convertible fixed income instrument. Strategies employ an investment process designed to isolate attractive opportunities between the price of a convertible security and the price of a non-convertible security, typically of the same issuer. Convertible arbitrage positions maintain characteristic sensitivities to credit quality the issuer, implied and realized volatility of the underlying instruments, levels of interest rates and the valuation of the issuer's equity, among other more general market and idiosyncratic sensitivities.

RV: Multi-Strategies

Relative value multi-strategies employ an investment thesis is predicated on realization of a spread between related yield instruments in which one or multiple components of the spread contains a fixed income, derivative, equity, real estate, MLP or combination of these or other instruments. Strategies are typically quantitatively driven to measure the existing relationship between instruments and, in some cases, identify attractive positions in which the risk adjusted spread between these instruments represents an attractive opportunity for the investment manager. In many cases these strategies may exist as distinct strategies across which a vehicle which allocates directly, or may exist as related strategies over which a single individual or decision making process manages. Multi-strategy is not intended to provide broadest-based mass market investors appeal, but are most frequently distinguished from others arbitrage strategies in that they expect to maintain >30% of portfolio exposure in 2 or more strategies meaningfully distinct from each other that are expected to respond to diverse market influences.

Composite Indices:

HFRI Fund Weighted Composite Index

The HFRI Fund Weighted Composite Index is a global, equal-weighted index of over 2,000 single-manager funds that report to HFR Database. Constituent funds report monthly net of all fees performance in US Dollar and have a minimum of $50 Million under management or a twelve (12) month track record of active performance. The HFRI Fund Weighted Composite Index does not include Funds of Hedge Funds.

HFRX Equal Weighted Strategies Index

The HFRX Equal Weighted Strategies Index is designed to be representative of the overall composition of the hedge fund universe. It is comprised of all eligible hedge fund strategies including but not limited to convertible arbitrage, distressed securities, equity hedge, equity market neutral, event driven, macro, merger arbitrage, and relative value arbitrage. The HFRX Equal Weighted Strategies Index applies an equal weight to all constituent strategy indices.

Appendix III: Return Unsmoothing

As discussed in Section 4.2 to mitigate return smoothing bias, and reconstruct the unsmoothed individual hedge fund returns this study adopts the methodology proposed by Getmansky, Lo and Makarov (2004).

The model of Getmansky et al. (2004) assumes that fund's observed return in period t (R_t^o) is a weighted average of the "true" returns (R_t^c) over the most recent $k+1$ periods, including the current period:

$$R_t^o = \theta_0 R_t^c + \theta_1 R_{t-1}^c + \cdots + \theta_k R_{t-k}^c \tag{III.1}$$

where $\theta_j \in [0,1], j = 0, \ldots, k$, $1 = \theta_0 + \theta_1 + \cdots + \theta_k$.

To estimate the θs, the following procedure is proposed. First, the observed returns are demeaned and a new time series is formed:

$$X_t = R_t^o - \mu \tag{III.2}$$

Second, by substituting R_t^o in (III.2) for (III.1) and replacing $R_t^c - \mu = \eta_t, R_{t-1}^c - \mu = \eta_{t-1}, \ldots, R_{t-k}^c - \mu = \eta_{t-k}$, (B.2) can be rewritten as:

$$X_t = \theta_0 \eta_t + \theta_1 \eta_{t-1} + \cdots + \theta_k \eta_{t-k} \tag{III.3}$$

where $1 = \theta_0 + \theta_1 + \cdots + \theta_k$

Getmansky et al. (2004) use an assumption that η_t are distributed normally, $\eta_t \sim N(0, \sigma_\eta^2)$, and estimate (III.3) as the $MA(k)$ process by maximum likelihood procedure. Further, the true returns R_t^c are recovered by inverting the equation (III.1):

$$R_t^c = \frac{R_t^o - \widehat{\theta_1} R_{t-1}^c - \cdots - \widehat{\theta_k} R_{t-k}^c}{\widehat{\theta_0}} \tag{III.4}$$

The unsmoothed and the observed returns have the same mean, but not the same variance. The variance of the unsmoothed returns is higher than that of the observed returns ($\sigma_c^2 \geq \sigma_o^2$).

Following other studies (Aragon, 2007; Getmansky et al., 2004; Jagannathan et al., 2010; Titman & Tiu, 2011) when implementing this procedure the parameter k is restricted to 1 (two-month smoothing) or 2 (quarterly smoothing).

Appendix IV: AIC Variable Selection

The appendix presents the AIC variable selection process adapted to GAM as described in Hastie (2013).

Algorithm IV.1 AIC Variable Selection

1. Initialize the model with the constant term[127].
2. Determine the regimen of each term F_j, for example $F_j = \{1, F_j\}, j = 1, \dots, N$, what means that predictor F_j can enter a model either as a constant or as a linear predictor.
3. Fit a series of models by moving each of the terms one step up or down in its regimen, relative to the formula of the current model. Keep a record of all the models ever visited, to avoid repetition.
4. Determine the "best" model in terms of the minimum value of the AIC statistic[128]. It defines one iteration of the algorithm.
5. Repeat steps 3 to 4 until either the maximum number of iterations has been used, or until the AIC cannot be decreased by any of the eligible shifts of the terms in their regimen.

[127] Alternatively, include all the potential predictors into the model

[128] Smaller values for the AIC indicate more preferable model

Appendix V: Fitting GAM with Loess Smoothers

This Appendix describes in more detail construction of a GAM using loess as a base smoother (loess GAM). Firstly, it provides a formal algorithm for fitting bivariate loess smoother, i.e. a loess smoother with a single predictor variable. Secondly, it gives the backfitting algorithm employed to fit a GAM with multiple predictors using bivariate loess smoothers.

Consider a problem of modelling a conditional expectation of response variable Y as a function of single predictor X:

$$E(Y|X) = f(X) \qquad \textbf{(V.1)}$$

The loess algorithm to estimate function f is as follows (R. A. Berk, 2008, p. 77):

Algorithm V.1 Loess Smoothing

1. Choose the smoothing parameter τ, which is a proportion between 0 and 1. Parameter τ is called bandwidth or span and controls smoothness of the function f.
2. Choose a point x_0 from X and from that the $\tau \times N = M$ nearest points on X, where N is the total number of observations.
3. For these M nearest neighbour points, compute a weighted least squares (WLS) regression line for Y on X[129]. The precise weight given to each observation depends

[129] In fact, it is possible to fit the polynomial of any degree, the regression should not be necessarily linear. However, the advantages gained in practice by using a quadratic or cubic form are not clear (R. A. Berk, 2008, p. 76).

on the weighting function (kernel). The tricube function[130] is a common choice with loess. Other weighting functions include the Gaussian kernel and the Epanechnikov (1969) kernel.

4. Construct the fitted value $\hat{y}_0$ for that single x_0.
5. Repeat steps 2 through 4 for each value of X.
6. Connect these $\hat{y}$s with a line.

Next, to estimate a GAM as in equation (5.5) which involves arbitrary number of predictors, individual loess smoothers can be combined together in such a way that accounts for potential correlations between predictors. To this end the algorithm V.1 is incorporated into an iterative statistical procedure developed to fitting additive models known as *backfitting algorithm* (Breiman & Friedman, 1985). In fact, backfitting algorithm closely resembles an iterative Gauss-Seidel algorithm for solving a system of equations.

The main idea is as follows. If the additive model (5.5) is correct, then for any F_k, $E\left(R_{i,t} - \alpha_i - \sum_{j\neq k} f_{i,j}\left(F_{j,t}\right) | F_k\right) = f_{i,k}(F_k)$. This immediately suggests an iterative algorithm for computing all smooth functions $f_{i,j}$, given the Algorithm V.1 that fits bivariate loess scatter smoothers (Hastie & Tibshirani, 1990).

Algorithm V.2 The Backfitting Algorithm

1. Initialize: $\alpha_i = mean\left(R_{i,t}\right), f_{i,j} = f_{i,j}^0, j = 1, \dots, N$.
2. Cycle: $j = 1, \dots, N, 1, \dots, N, \dots$.

   $f_{i,j} = lo(R_{i,t} - \alpha_i - \sum_{k\neq j} f_{i,k} | F_j)$, where lo refers to loess smoothing according to Algorithm V.1.

[130] The tricube function is defined as $f(z) = (1 - |z|^3)^3 \times I(|z| < 1)$, where z is the standardized difference between x_0 and each x.

3. Continue step 2 until the individual functions do not change or maximum number iterations reached.
4. Repeat step 1-3 for each hedge fund style $i, i = 1, \ldots, M$.

Essentially when constructing a smoothing function $f_{i,j}$ backfitting algorithm controls for the effect of all other functions $f_{i,k}$, $k \neq j$. Hastie and Tibshirani (1990, p. 92) ascertain it has good converging properties in most of the practical situations.

Appendix VI: Component-Wise Gradient Boosting

This appendix outlines component-wise gradient boosting technique (Friedman, 2001; Hofner, Hothorn, Kneib, & Schmid, 2011; Hofner, Mayr, Robinzonov, & Schmid, 2014) used for estimation and variable selection of a robust linear regression model and a robust GAM.

Consider datasets containing the values of an outcome variable y and predictors $x_1, \dots, x_p$. The aim is to model the relationship between y and $\mathbf{x} := \left(x_1, \dots, x_p\right)^{\mathrm{T}}$ and to obtain an "optimal" prediction of y given $\mathbf{x}$. This is accomplished by minimizing the loss function $\rho(y, f) \in \mathbb{R}$ over a prediction function f (depending on $\mathbf{x}$). To model conditional median, the loss function is set to be absolute loss, i.e. $\rho(y, f) = |y - f|$.

In the gradient boosting framework, the aim is to estimate the optimal prediction function f^*, that is defined by

$$f^* := argmin_f E[\rho(y, f(\mathbf{x}^{\mathrm{T}}))]$$

In practice the expectation is substituted with the observed mean of the loss function, also known as "empirical risk": $\mathcal{R} := \sum_{i=1}^{n} \rho(y, f(\mathbf{x}_i^{\mathrm{T}}))$. The following algorithm is used to minimize $\mathcal{R}$ over f:

Algorithm VI.1 Component-Wise Gradient Boosting

1. Initialize the function estimate $\hat{f}^{[0]}$ with offset values. To model conditional median offset may be set to the median of the response variable.

2. Specify a set of base-learners. For example, for a median regression linear base-learners can be used, and for a GAM penalized splines can be applied. Denote the number of base-learners as P and set $m = 0$.
3. Increase m by 1, where m is the number of iterations.
4. a) Compute the negative gradient $-\frac{\partial \rho}{\partial f}$ of the loss function and evaluate it at $\hat{f}^{[m-1]}(\mathbf{x}_i^{\mathrm{T}}), i = 1, \dots n$ (i.e. at the estimate value from the previous iteration)[131]. This yields the negative gradient vector:

$$\mathbf{u}^{[m]} = \left(u_i^{[m]}\right)_{i=1,\dots n} := \left(-\frac{\partial}{\partial f}\rho\left(y_i, \hat{f}^{[m-1]}(\mathbf{x}_i^{\mathrm{T}})\right)\right)_{i=1,\dots n}.$$

   b) Fit each of P base-learners to the negative gradient vector. The resulting P regression yield P vectors of predicted values, where each vector is an estimate of the negative gradient vector $\mathbf{u}^{[m]}$.

   c) Select base-learner that fits $\mathbf{u}^{[m]}$ best according to the residual sum of squares (RSS) criterion and set $\hat{\mathbf{u}}^{[m]}$ equal to the fitted values of the best-fitting base-learner.

   d) Update current estimate by setting $\hat{f}^{[m]} = \hat{f}^{[m-1]} + \nu\hat{\mathbf{u}}^{[m]}$ where $0 < \nu \leq 1$ is a real-valued step length factor, also called a learning rate.

5. Iterate Steps 3 and 4 until the number of iterations reaches the stopping number m_{stop}.

As seen from steps 4(c) and 4(d), the algorithm automatically carries out variable selection and model choice, as only one base-learner is selected for updating $\hat{f}^{[m]}$ in each iteration.

[131] Absolute loss function is not differentiable at $y = f$ and the value of negative gradient at such points is fixed at zero.

Due to the additive update, the final boosting estimate at iteration m_{stop} can be interpreted as an additive prediction function, i.e.:

$$\hat{f} = \hat{f}_1 + \dots + \hat{f}_P,$$

where $\hat{f}_1, \dots \hat{f}_P$ correspond to functions specified by base-learners. Some of the $\hat{f}_j, j = 1, \dots P$ might be equal to zero, as the corresponding base-learners might not have been selected in step 4(c).

Appendix VII: Fitting MARS

This appendix outlines the fitting procedure for a multivariate adaptive regression splines (MARS) model.

A MARS model has the following form (Hastie et al., 2004, p. 284):

$$f(X) = \beta_0 + \sum_{m=1}^{M} \beta_m h_m(X) \qquad \textbf{(VII.1)}$$

where $h_m(X)$ are basis functions, known as hinge functions, from the set C or a product of two or more such functions, where set C is defined as follows: $C = \left\{ \left(X_j - t\right)_+, \left(t - X_j\right)_+ \right\}_{t \in \{x_{1j}, x_{2j}, \ldots, x_{Nj}\}, j=1,2,\ldots,p}$.

Given the choice of functions h_m, the coefficients β_m are estimated by standard ordinary least squares (OLS) procedure. A MARS approach builds a model in two phases: the forward and the backward pass.

Forward pass

Start with $h_0(X) = 1$ in the model and all functions in the set C are candidate functions. At each step consider as a new basis function a pair of all products of function h_m in the model set $\mathcal{M}$ with one of the reflected pairs in C. Add to the model $\mathcal{M}$ the term of the form

$$\hat{\beta}_{M+1} h_l(X)\left(X_j - t\right)_+ + \hat{\beta}_{M+2} h_l(X)\left(t - X_j\right)_+, h_l \in \mathcal{M} \qquad \textbf{(VII.2)}$$

which produces the largest decrease in training error. $\hat{\beta}_{M+1}$, $\hat{\beta}_{M+2}$ and all other coefficients are estimated by least squares. The winning products are added to the model and the process in continued until the model set $\mathcal{M}$ contains the preset maximum number of terms or numerical accuracy limit is reached (no new terms decrease the error). The maximum number of terms n_{max} is calculated using the formula (Milborrow, 2012):

$$n_{max} = \min(200, \max(20{,}2 * Number\ of\ Predictors)) + 1 \quad \textbf{(VII.3)}$$

Using this formula the maximum number of terms in the six-factor and 14-factors MARS models will not exceed 21 and 29 respectively. These limits set a reasonable trade-off between the model flexibility and complexity, given that in the study of Giannikis and Vrontos (2011) the maximum number of terms in a threshold linear regression hedge fund pricing model is found to be 12.

A constraint on the degree of the model $\mathcal{M}$ can be imposed by limiting potential products of the basis functions. For example, in the first degree MARS, considered in this thesis, there are no interaction terms and all the predictor have linear form.

Backward (pruning) pass

The forward pass typically leads to a large model which overfits the data, and so a backward deletion procedure is applied. It removes sequentially those terms which lead to the smallest increase in residual squared error. Model subsets are compared using the GCV criterion. The GCV is a form of model regularization: it trades off goodness-of-fit against model complexity. The GCV is calculated as:

$$GCV = \frac{RSS}{N(1 - Effective\ Number\ of\ Parameters/N)^2} \quad \textbf{(VII.4)}$$

where RSS is the residual sum of squares and the effective number of parameters is defined in the MARS as follows:

$$Effective\ Number\ of\ Parameters = Number\ of\ MARS\ Terms + Penalty \times \\ \times (Number\ of\ MARS\ Temrs - 1)/2 \quad \textbf{(VII.5)}$$

where penalty equals two for first degree MARS and three for higher degree models. The GCV formula (VII.4) penalizes additional terms. Thus, it adjusts the training RSS to take into account the flexibility of the model.

Appendix VIII: Performance of Funds Sorted by Form of Systematic Risk Exposures Based on Six-Factor Models

Table VIII.1 Performance Characteristics of Funds Sorted by Form of Exposure to Systematic Risk

The table presents performance characteristics of individual funds sorted by style and form of exposure to six HL6 factors during the period 1995-2009.

Style	Exposure	Sharpe	Δ Sharpe	t-stat	ES	Δ ES	t-stat	Alpha	Δ Alpha	t-stat	Appraisal	Δ Appraisal	t-stat
CA	Linear	1.5475			-0.0688			0.0014			-0.1061		
	Nonlinear	1.0656	-0.482*	-1.7137	-0.1173	-0.0485***	-2.8837	-0.0006	-0.0020	-1.6656	-0.0467	0.0593	0.5039
	None	3.8937	2.3462***	3.1438	-0.0201	0.0487***	4.6836	-0.0006	-0.002*	-1.8197	-0.1885	-0.0825	-0.5946
DSB	Linear	0.0207			-0.1273			-0.0009			0.0085		
	Nonlinear	0.0162	-0.0044	-0.0224	-0.1109	0.0164	0.3521	-0.0027	-0.0018	-0.6513	-0.0814	-0.0899	-1.2040
	None	0.4094	0.3887	1.1426	-0.2547	-0.1274	-1.1751	0.0098	0.0107***	4.1311	0.2558	0.2473	1.8627
EM	Linear	0.6817			-0.1523			0.0010			-0.0353		
	Nonlinear	0.5075	-0.1742*	-1.9353	-0.1461	0.0062	0.4019	-0.0043	-0.0053***	-4.9304	-0.2186	-0.1833***	-5.1703
	None	1.3027	0.621***	3.3235	-0.1406	0.0118	0.4576	0.0010	0.0001	0.0296	-0.0699	-0.0345	-0.7033
EMN	Linear	1.0187			-0.0646			0.0007			-0.1270		
	Nonlinear	0.2784	-0.7403***	-3.9976	-0.0854	-0.0208**	-2.2434	-0.0024	-0.0031***	-3.3822	-0.1484	-0.0214	-0.2254
	None	1.7767	0.758**	2.5568	-0.0399	0.0247***	3.3956	0.0004	-0.0003	-0.2922	-0.0798	0.0472	0.4591
ED	Linear	1.3948			-0.0602			0.0007			0.0115		
	Nonlinear	1.0321	-0.3627**	-2.1186	-0.0879	-0.0276***	-3.9514	-0.0016	-0.0022***	-3.8853	-0.1215	-0.133***	-5.1386
	None	2.1205	0.7258***	4.0036	-0.0404	0.0198***	3.3189	-0.0003	-0.0009	-1.0618	-0.0773	-0.0888**	-2.1212
FIA	Linear	1.8685			-0.0622			0.0007			0.0138		
	Nonlinear	1.4258	-0.4427	-0.7682	-0.1180	-0.0558**	-2.0860	0.0006	-0.0002	-0.1316	-0.0279	-0.0417	-0.5362
	None	2.7082	0.8397*	1.6718	-0.0480	0.0141	0.8839	-0.0008	-0.0016	-1.5964	-0.2487	-0.2624**	-2.3927
GM	Linear	0.8026			-0.0824			0.0004			-0.0238		
	Nonlinear	0.8286	0.0260	0.1808	-0.0910	-0.0086	-0.5869	0.0017	0.0013	0.6620	-0.0010	0.0228	0.4533
	None	0.8639	0.0613	0.5513	-0.0690	0.0134	1.5384	-0.0007	-0.0011	-0.9343	-0.0321	-0.0083	-0.2423
LSE	Linear	0.7593			-0.0984			-0.0001			-0.0248		
	Nonlinear	0.6358	-0.1234*	-1.9289	-0.1209	-0.0226***	-2.7881	-0.0003	-0.0002	-0.2259	-0.0532	-0.0284	-1.5111
	None	1.0271	0.2678***	5.6688	-0.0829	0.0155***	3.1222	0.0006	0.0007*	1.8097	-0.0228	0.0021	0.1696

MF	Linear	0.8539			-0.1163			-0.0003			-0.0393		
	Nonlinear	0.7313	-0.1226	-0.6008	-0.0989	0.0174	1.4060	-0.0003	0.0000	-0.0210	-0.0303	0.0090	0.2905
	None	1.0984	0.2444	0.9891	-0.1053	0.0109	1.0027	-0.0002	0.0001	0.1153	0.0112	0.0505*	1.8024
MS	Linear	1.0976			-0.0709			-0.0002			-0.0124		
	Nonlinear	1.0679	-0.0297	-0.1275	-0.0952	-0.0244**	-2.0708	-0.0015	-0.0013	-1.2309	-0.0918	-0.0794	-1.4984
	None	3.4900	2.3924***	6.8225	-0.0419	0.0289***	3.9445	0.0009	0.0011	1.6461	0.2261	0.2386***	4.0804
FoF	Linear	0.9362			-0.0554			0.0002			0.0013		
	Nonlinear	0.4625	-0.4737***	-8.0833	-0.0679	-0.0125***	-6.3317	-0.0013	-0.0015***	-7.5187	-0.1019	-0.1032***	-4.6170
	None	2.1268	1.1905***	8.9619	-0.0450	0.0104***	3.8145	0.0009	0.0007**	2.5760	0.1607	0.1594***	4.6023
Overall	Linear	0.9206			-0.0801			0.0002			-0.0153		
	Nonlinear	0.6192	-0.3014***	-7.3385	-0.0863	-0.0062***	-2.6350	-0.0012	-0.0014***	-7.0152	-0.0932	-0.0779***	-6.5856
	None	1.7717	0.8511***	12.9444	-0.0662	0.0139***	5.6594	0.0005	0.0003	1.5421	0.0387	0.0539***	3.6850

Appendix IX: Cumulative Performance of TASS Indices and Replicating Portfolios

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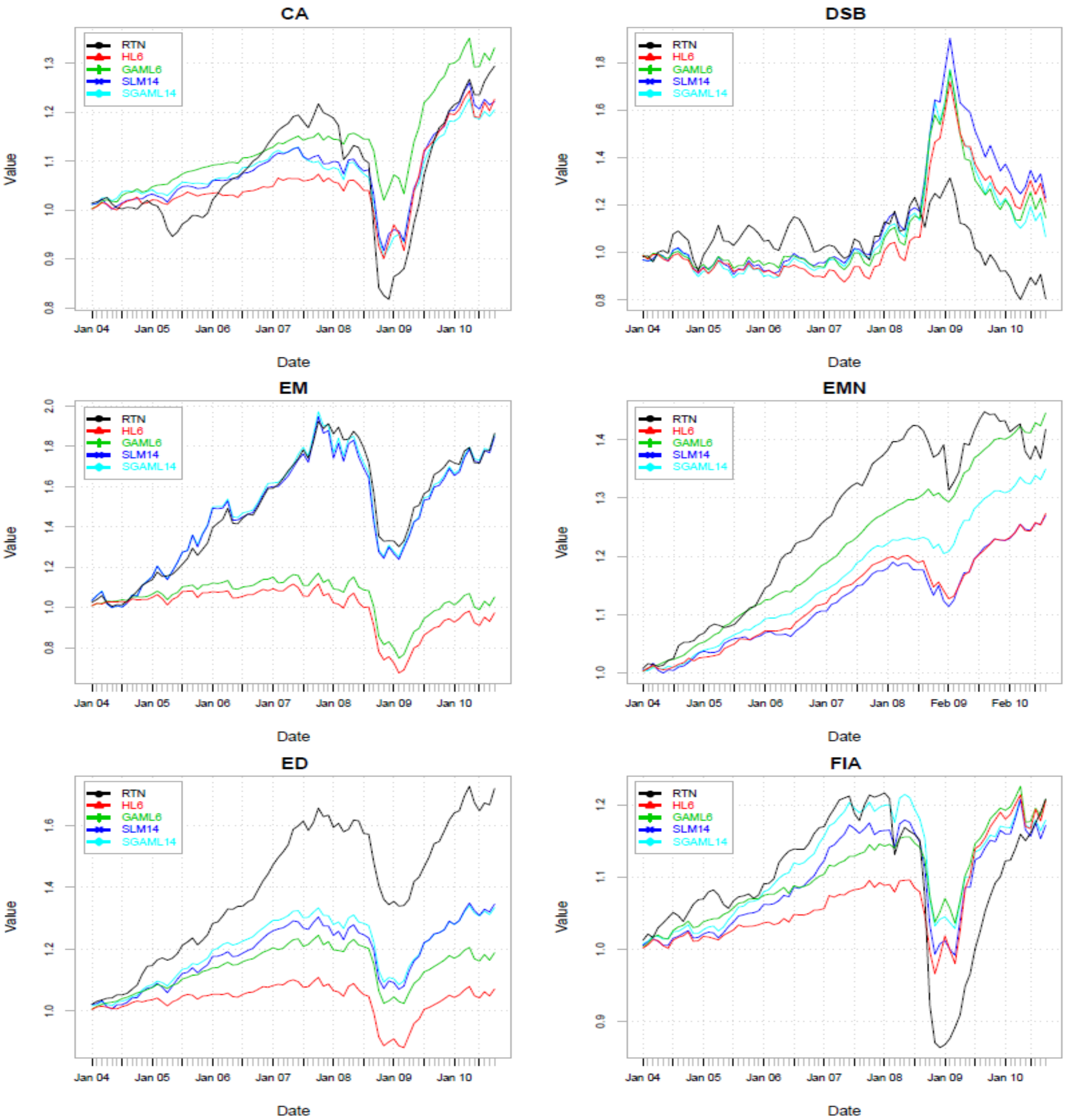
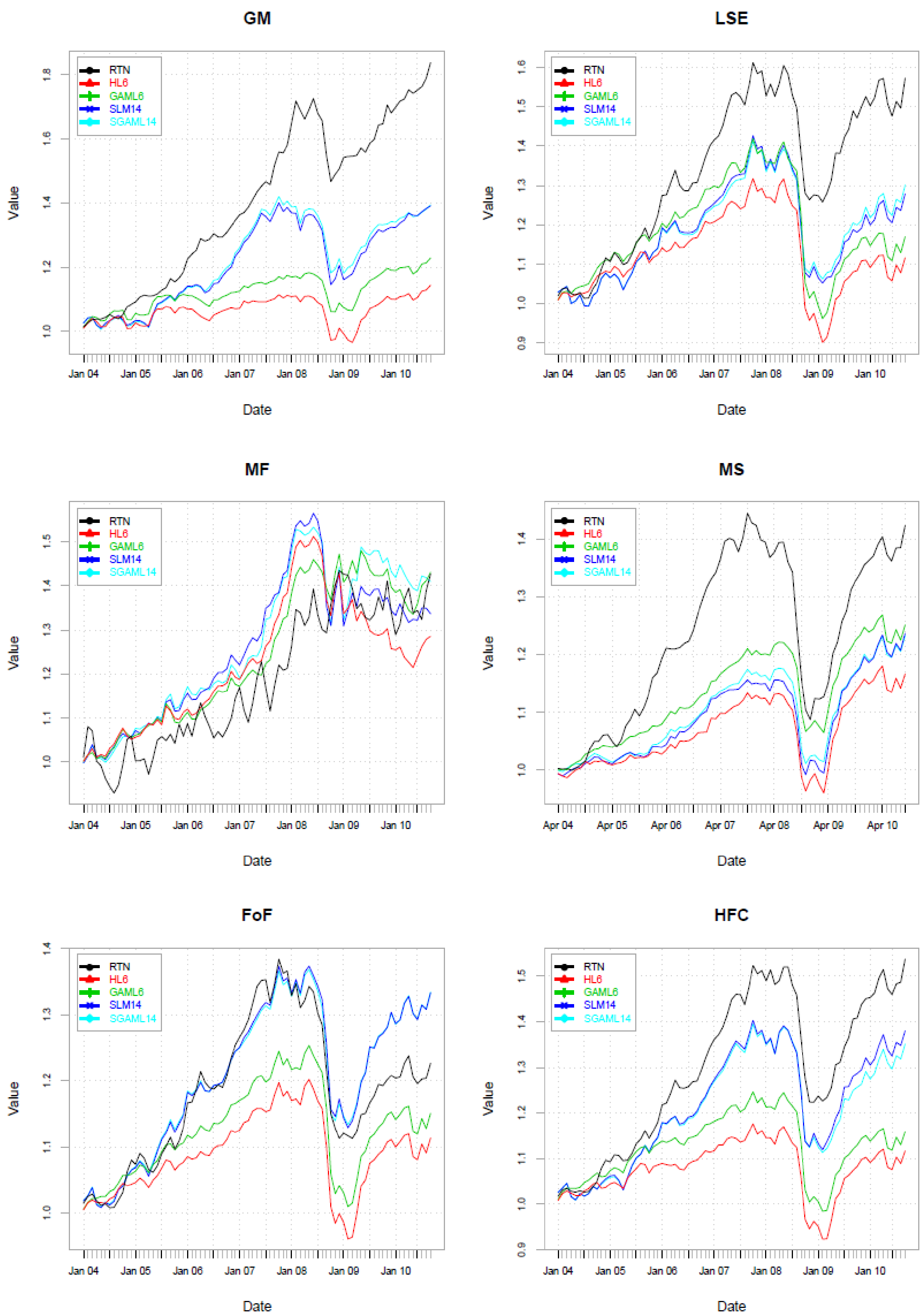
Figure IX.1 Cumulative Performance of TASS Style Indices and Replicating Portfolios

The graphs show cumulative performance of TASS style indices (black colour solid line, denoted as RTN) and their linear and nonlinear clones during the out-of-sample period from January 2004 to September 2010. Clones are constructed based on four models, the linear HL6 and SLM14 models, and the nonlinear GAML6 and SGAML14 using a rolling window procedure.




GM
LSE
MF
MS
FoF
HFC
RTN
HL6
GAML6
SLM14
SGAML14
Value
Date
Jan 04
Jan 05
Jan 06
Jan 07
Jan 08
Jan 09
Jan 10
Apr 04
Apr 05
Apr 06
Apr 07
Apr 08
Apr 09
Apr 10