CSIRO-Monash Superannuation Research Cluster

WORKING PAPER SERIES

PASSIVE HEDGE FUNDS

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14 September 2016

CSIRO-MONASH WORKING PAPER NO 2016-06

CLUSTER PROJECT 4: BETTER SUPERANNUATION OUTCOMES: FUND INDEXING, STYLE AND HEDGE FUNDS

ABSTRACT

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ACKNOWLEDGEMENTS: THIS RESEARCH WAS SUPPORTED BY THE CSIRO-MONASH SUPERANNUATION RESEARCH CLUSTER, A COLLABORATION BETWEEN CSIRO, MONASH UNIVERSITY, GRIFFITH UNIVERSITY, THE UNIVERSITY OF WESTERN AUSTRALIA, THE UNIVERSITY OF WARWICK, AND STAKEHOLDERS OF THE RETIREMENT SYSTEM IN THE INTEREST OF BETTER OUTCOMES FOR ALL.

Passive Hedge Funds

by

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The research was funded by the CSIRO-Monash Superannuation Research Cluster, a collaboration across institutions and industry, among stakeholders of the retirement system in the interest of better outcomes for all.

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Abstract

We show that most hedge fund managers are passive, not active. Active management should be manifest through nonlinear exposure to the systematic risk factors that drive hedge fund returns which leads to enhanced performance. We find that approximately two-thirds of hedge funds exhibit only linear factor exposures and hence are "passive". What's more, such "passive" managers tend to outperform "active" managers. Finally, we also show that many "active" managers, despite initial nonlinear risk exposures, eventually become "passive".

The question at the heart of this study is simple: do most hedge fund managers generate returns through managerial skill? The answer, according to our work is no. Most hedge fund managers rely on “passive” linear risk exposures to generate their returns and, paradoxically, they outperform most “active” managers which try to deploy skill.

To demonstrate skill, a hedge fund manager must generate enhanced performance through active management. Active strategies, such as market timing, in contrast to passive buy and hold strategies should be manifest through nonlinear exposure to the systematic risk factors (Merton, 1981) that drive hedge fund returns and as a consequence of active management outperformance should ensue. In this study we ascertain whether nonlinear systematic risk exposures drive hedge fund returns, and if so, what economic outperformance is generated as a consequence.

Prior work has challenged the notion of hedge fund managers possessing skill (Fung and Hsieh 1997; Hasanhodzic and Lo 2007), suggesting instead that they extract a significant part of their returns from “passive” linear systematic risk exposures.

We estimate whether the hedge fund systematic risk factor exposure driving hedge fund returns are linear or nonlinear. We use the same systematic risk factors (i.e., explanatory variables) as used in a popular linear factor model — the six-factor Hasanhodzic and Lo (2007) model (HL6) — as well as factors derived from Agarwal and Naik (2004) and from Vrontos, Vrontos, and Giamouridis (2008).

We obtain some interesting results: First, we show that when hedge funds are grouped in style portfolios, nonlinear risk exposures are more pronounced in styles that focus on exploiting arbitrage opportunities and relative security mispricing, consistent with the findings of Mitchell and Pulvino (2001), Fung and Hsieh (2002b), and Agarwal and Naik (2004). Second, we investigate the prevalence of nonlinear patterns in risk exposures of individual funds and find that the majority of funds, roughly two-thirds, exhibit only linear exposures, while nonlinear features are present in the exposures of around one-fifth of funds; the rest of the funds have insignificant exposures to any systematic risk factors and are deemed to be market-neutral funds. Third, in order that we may evaluate the impact of nonlinear risk exposures on hedge fund performance, we construct three portfolios of funds for each style: a portfolio of exclusively linear exposed funds; another of nonlinear exposed funds; and, a final portfolio of market-neutral funds. Here, our results suggest that nonlinear funds are (on average) inferior to linear funds in terms of raw and risk-adjusted returns and also have higher negative tail risk. This provides evidence against hedge fund managers' claims of skill leading to superior returns. Finally, we also analyse the persistence of hedge funds to risk exposures in an attempt to verify whether performance patterns observed among nonlinear, linear, and market-neutral funds can be exploited by investors to generate profits; we find that the majority of nonlinear funds that survive over the long term tend to alter their risk exposures and eventually become linear funds.

In conclusion, consistent with the notion of efficient markets removing abnormal profits, our results suggest that most hedge funds are "passive" and generate returns consistent with linear risk factor exposures. Paradoxically, such "passive" hedge funds outperform "active" hedge funds which have nonlinear factor exposures.

1. Literature Review

Most recent academic work is unclear about whether nonlinearities exist in hedge fund returns and, if so, what economic "value add" results from modeling these nonlinearities. In this literature review, we ultimately narrow our focus to the three key studies of nonlinearities in hedge fund returns: Amenc et al. (2010), Diez de los Rios and Garcia (2011), and Giannikis and Vrontos (2011). These papers reach quite different conclusions about the presence of nonlinearities in hedge fund returns.

However, we start with the formative work on nonlinearity in hedge fund returns using options. Fung and Hsieh (2001) argue that, theoretically, a payoff of an actively managed fund that can perfectly predict price trends resembles a payoff of a *lookback straddle*[1]. They call the optimal trend-following strategy of buying lookback straddles the "Primitive Trend-Following Strategy" (PTFS). The authors construct PTFS factors for stocks, bonds, interest rates, and currency and commodity markets, and they show that returns of commodity trading advisors (CTAs), a popular hedge fund strategy, are well explained by these factors. Furthermore, Fung and Hsieh (2004) combine three PTFS factors (for bonds, currencies, and commodities) with four conventional asset-based style (ABS) factors and propose a pricing model for any hedge fund. This model is widely known in the literature as the seven-factor Fung and Hsieh (FH7) model.

Agarwal and Naik (2004) also use options for modelling hedge fund returns and propose the option-based hedge fund factor model. This model builds on the seminal work of Henriksson and Merton (1981) as well as studies of Breeden and Litzenberger (1978) and Glosten and Jaganathan (1994), who use option contracts to characterize nonlinearities. Agarwal and Naik (2004) employ a stepwise regression procedure to identify the set of relevant option contracts, while exogenously setting option parameters (e.g., strike price). They conclude that the option-

[1] A lookback straddle is a combination of long positions in lookback call and put options. A lookback call/put option is a contract that 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.

augmented model is able to capture the dominant economic risk exposures of hedge funds, which often have a nonlinear form. 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). Therefore, they suggest that 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.

However, the approach and testing methodology in Agarwal and Naik (2004) has been criticized in Diez de los Rios and Garcia (2011). The first issue raised is related to the choice of option contracts in Agarwal and Naik (2004) which assumes that hedge funds hold the same portfolio of options on the same underlying asset and the same strike price. In addition, the sequential procedure of adding and deleting option-based factors (which have non-normal distributions) makes it impossible to rely on standard statistical inference for variable selection. Consequently, Diez de los Rios and Garcia (2011, p. 196) argue that due to the 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 artifact."

Diez de los Rios and Garcia (2011) correct the statistical testing methodology and develop a data-dependent procedure for automatic selection of the underpinning option's strike price. They also estimate the value of the nonlinear features of hedge funds. Their results reveal that only one fund out of two provides significant positive performance to its investors and linear specification tests indicate that there is statistical support for rejecting linearity in three hedge fund styles out of ten. Furthermore, at the individual fund level, nonlinearities are supported statistically for only one-fifth of funds. These findings are unexpected given the evidence of nonlinearities in hedge fund portfolios in prior studies. It suggests that nonlinear features are not overly important.

Amenc, Martellini, Meyfredi, and Ziemann (2010) also question the efficiency of option portfolios in hedge fund return modeling. They argue that although the introduction of arbitrary option portfolios can improve the model's in-sample explanatory power, nothing guarantees that the chosen underlying assets and their parameters accurately represent the true state-dependent factor exposure of hedge fund managers. Amenc et al. (2010) perform an out-of-sample test of the linear model, the option augmented model, and two conditional models based on a Markov regime-switching approach as well as a Kalman filtering approach. First, they find that the out-of-sample model fit does not vary significantly across different factor model implementations. Second, 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 two models perform equivalently) the option augmented model has consistently higher tracking error and lower correlation compared to the corresponding linear model. The negative effect of option-based factors on the out-of-sample fit is attributed to statistical estimation difficulties. Third, other dynamic models also do not generate a better quality of fit than the linear model. The authors' overall conclusion is that nonlinear models, which are less parsimonious than their linear counterparts, do not necessarily lead to improved out-of-sample model performance.

Finally, Giannikis and Vrontos (2011) examine nonlinearities using a flexible threshold risk factor model. This model allows for multiple 'breakpoints' in risk factor exposures. The results suggest that different hedge fund strategies exhibit nonlinear relations to different risk factors. Nonlinearities are observed in twelve hedge fund styles out of the thirteen examined. In some styles (e.g., the Quantitative Directional and the Fixed Income Corporate), the model identifies multiple threshold values. This suggests, that the failure of option-based models in an out-of-sample tests (Amenc et al., 2010) is likely to be due 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 in hedge funds.

To conclude, the most recent academic work is unclear about whether nonlinearities exist in hedge fund returns Even if nonlinear systematic risk exposures are a genuine driver of hedge fund returns, it is also unclear whether any economically meaningful outperformance is generated as a consequence. We attempt to resolve these issues in our work.

2. Methodology

Next, we introduce the methodology and show whether the relation between hedge fund returns and those systematic risk factors used in traditional linear factor models is, in fact, nonlinear.

We start by analyzing nonlinear patterns in hedge fund style portfolios. Aggregated portfolio analysis generates less noise than analysis conducted on individual funds. However, aggregation may also lead to biases, as it may either create 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 (Diez de los Rios & Garcia, 2011). Therefore, we also consider individual hedge funds.

2.1 Nonlinearities in Hedge Fund Style Portfolios

The extant literature on hedge funds has documented a number of nonlinear patterns in risk exposures of aggregate hedge fund style portfolios.

Consistent with this prior literature, we postulate a nonlinear model for hedge fund returns, R. In the nonlinear multi-factor model each factor exposure is modelled by a flexible risk function $f(F_i)$, which determines the relation between risk factor returns and fund's returns:

$$E[R] = \alpha + \sum_{i=1}^{m} f(F_i) \tag{1}$$

The model in equation (1) preserves the additive form of a linear multi-factor model; thus, the impact of each factor can be evaluated independently as in a linear model. However, in contrast to a linear regression, risk functions $f(F_i)$ can take any linear or nonlinear form and are estimated non-parametrically. We use two types of nonlinear risk functions to estimate $(.)$: the first type is based on loess smoothers, and the second type is based on cubic splines[2].

Furthermore, we use three linear models as benchmarks for nonlinear models: the seven-factor Fung and Hsieh model, FH7, a linear model with six factors from Hasanhodzic and Lo (2006), HL6, and a stepwise linear model with 14 risk factors (see Section 4). The FH7 model is currently the most widely accepted hedge fund pricing model. The HL6 model is appealing because it includes a simple and intuitive set of six risk factors (see Section 4). A stepwise linear model is also frequently exploited in the literature as it helps to identify a parsimonious model. The complete list of models is given in Table 1.

[2] There is a well-established technology in the applied statistics literature, which we use to estimate nonlinear hedge fund risk factor exposures, known as Generalized Additive Models (see Hastie and Tibshirani (1990) and Wood (2006)). In particular, we use two forms of GAMs with loess smoothing functions, and cubic splines. For GAMs with loess functions we apply a stepwise selection procedure based on\an AIC criterion. Each term in the model is either included in the model in a linear or nonlinear form or dropped from the model. For GAMs with cubic splines, variable selection is can be performed automatically as part of the fitting algorithm. In order to consider separately the impact of automatic variable selection procedures and additional flexibility of GAMs, we test versions of GAMs with and without variable selection.

<<Insert Table 1>>

To evaluate the models, we use a rolling window with a 120-month estimation window and a one-month forecast window. The size of the estimation window is chosen to be sufficient to estimate the data-hungry nonlinear models with precision. In the other hedge fund literature, the window size varies. Giamouridis and Paterlini (2010) also utilized a 120-month estimation window for linear models; Giannikis and Vrontos (2011) employed recursive windows expanded by one month starting from 192 months; Amenc, El Bied, and Martellini (2003) estimated models based on 60 observations; and Hasanhodzic and Lo (2007) relied on a 24-month rolling window. Our tests not reported here[3] suggest that for most of the styles, performance of both nonlinear and linear models improves with the size of the estimation window. Therefore, we are confident that the choice of a quite large window does not adversely affect linear models.

2.2 Nonlinearities in Individual Funds

After analysing nonlinearities in hedge fund style portfolios, our next aim is to evaluate the pervasiveness of nonlinear features in risk exposures of individual hedge funds and to assess their influence on funds' performance. The nonlinear and linear models are fitted using individual funds' returns[4] and all funds are classified into three categories: linear, nonlinear, and market-neutral funds. To avoid the issues of data snooping and multiple hypothesis testing bias (given the large number of funds), we follow a procedure[5] similar to one utilized by Bollen (2013).

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[3] Available from the authors upon request.

[4] In related work Lajbcygier & Tupitsyn (2017) shows that as a consequence of successfully mimicking the systematic risk exposures that drive hedge fund returns, linear and nonlinear hedge fund clones exhibit lower tracking error and substantially higher raw and risk-adjusted returns than both investable and non-investable hedge fund indices.

[5] The procedure is as follows: (1) Obtain critical values of model's goodness of fit statistic (adjusted R^2) via a bootstrap simulation procedure. 1,000 random samples of 120 observations each are generated 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 the bootstrap with resampling. The linear model is fitted first and the average value of the 95th percentile

After funds are classified, portfolios of linear, nonlinear, and market-neutral funds are formed and their performance characteristics are compared during three five-year periods (1995-1999, 2000-2004, 2005-2009). We are interested to test whether funds with nonlinear risk exposures performed better than linear and market-neutral funds during these periods. The choice of these three periods is due to the availability of data[6] and the minimum window lengths required to estimate the nonlinear model.

Finally, the last question we investigate is persistence in fund risk exposure. This is an important question because it helps to clarify whether knowledge of a fund's risk exposure in the past can help investors make informed decisions in the future. We analyze persistence in a two-period setting by using a five-year window of data to calculate transition probabilities, which determine the likelihood of a fund moving from one set of risk exposures to another in the next period. We apply Cohen's kappa coefficient (Cohen, 1960) to measure persistence of the linear, nonlinear, and neutral forms of exposure over the two periods.

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of the R^2 coefficient across all samples is recorded. Then the nonlinear model is fitted to the residuals of the linear regression model and the average 95th percentile of R^2 is calculated. (2) Funds are classified into three sub-categories for each style: funds with only linear exposures, funds that have nonlinear exposures, and funds with insignificant exposures. The linear model is fitted first and then the nonlinear model is fitted to the residuals of the linear model, and the linear and nonlinear models' R^2 coefficients are evaluated against critical values. A fund is classified as a linear fund if it has significant linear R^2 coefficient only (i.e., above the critical value); as a nonlinear fund if its nonlinear R^2 coefficient is significant; and as a market-neutral fund otherwise. We determine fund class for all the funds with sufficient data during three five-year periods using six and 14-factor models: 1995-1999, 2000-2004, and 2005-2009.

[6] The authors had individual fund's data only until 2009

3. Data

We use the Credit Suisse/TASS database covering the period from January 1994 to September 2010 in this study. TASS database includes hedge fund indices for 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), and Fund of Funds (FoF) styles as well as a composite hedge fund index (HFC). The dataset with individual funds for the analysis of nonlinearities at fund level is sourced from the TASS "Live" and "Graveyard" databases containing active and defunct funds. Filters are applied to the data to exclude funds that (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; or (v) have fewer than 60 monthly returns. The minimum requirement of 60-month history is necessary to estimate linear and nonlinear models. The final sample consists of 5,580 hedge funds, of which 2,670 are active and 2,910 are defunct.

Hedge fund databases are known to have multiple biases, which have been extensively discussed in the literature. These biases include survivorship bias, instant history or backfilling bias, self-selection bias, and stale price bias (Aiken, Clifford, & Ellis, 2013; Baquero, Horst, & Verbeek, 2005; Brown, Goetzmann, Ibbotson, & Ross, 1992; Fung & Hsieh, 1997, 2000, 2002a; Getmansky, Lo, & Makarov, 2004; Liang, 2000). Survivorship bias occurs when hedge funds that stopped reporting to a database vendor are excluded from the database. To mitigate survivorship bias, we include funds from the TASS "Graveyard" database, which stores historical data on all defunct funds. Instant history or backfilling bias arises because some funds backfill historical returns when they first enter the database. In the TASS database, backfilled data can be identified by the field that shows when the fund first joined the database. Accordingly, in this study all backfilled returns have been truncated. Self-selection bias occurs due to funds' voluntary decision to report (or not to report) to the database. It is argued that this practice may create an upward bias, because funds have incentive to report only when their performance is good. However, it has been recently suggested that many top-performing funds also do not report to hedge fund databases, because as they reach their target size they no longer need publicity to attract new investments (Fung & Hsieh, 2009). Therefore, these two effects offset each other, and self-selection bias is likely to be small for practical purposes (Edelman, Fung, & Hsieh, 2013; Fung & Hsieh, 2009). Another serious bias is return smoothing. It occurs due to a number of factors, including stale pricing of hedge funds' illiquid holdings, the option-like structure of incentive fee contracts, and time-varying leverage, and it causes serial correlation in hedge fund returns (Getmansky, Lo, & Makarov, 2004). This bias is particularly important for this study, because using net-of-fees returns reported in the TASS database may attenuate nonlinear patterns in hedge funds' risk exposures. To address this issue, we follow the procedure developed by Getmansky et al. (2004); we reconstruct unsmoothed returns series and use them in our analysis.

Next, we briefly discuss the data on risk factors. With regards to the variables for hedge fund models, we have chosen three sets of risk factors:

- The seven factors of Fung and Hsieh (2004b): PTFS on bonds (PTFSBD), currencies (PTFSFX), and commodities (PTFSCOM); the equity market premium (SNPMRF); the size spread (SCMLC); the change in the U.S. Federal Reserve 10-year constant maturity yield (T10Y); and the credit spread (CREDSPR).
- The six factors of Hasanhodzic and Lo (2007): the US Dollar Index return (USD); the return on the Barclays/Lehman Corporate AA Intermediate Bond Index; the spread

between the Lehman BAA Corporate Bond Index and the Lehman Treasury Index (BOND); the S&P 500 total return (SP500); the Goldman Sachs Commodity Index total return (GSCI); and the first-difference of the end-of-month value of the CBOE Volatility Index (DVIX).

- An extended set of Hasanhodzic and Lo (2007) variables augmented with another eight factors identified from the literature (Agarwal, Fung, Loon, & Naik, 2011; Agarwal & Naik, 2004; Vrontos, Vrontos, & Giamouridis, 2008): Fama and French's (1993) size (SMB) and book-to-market (HML) factors; 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).

As explained in the introduction section, the FH7 and HL6 models have often been cited and used in the hedge fund literature. The rest of the factors follow from the models of Agarwal and Naik (2004), Vrontos et al. (2008), and Agarwal et al. (2011). They also have been utilized in a closely related recent study on hedge fund nonlinearities by Giannikis and Vrontos (2011).

4. Results

In this section, we consider the results of nonlinear risk exposures in hedge fund styles. In particular, we consider which risk factors best explain various hedge fund style returns, examine evidence for nonlinear hedge fund exposures to risk factors, and consider the persistence of nonlinear risk exposures in hedge fund performance.

4.1 Nonlinear Risk Exposures in Hedge Fund Styles

Table 2 presents summary statistics for TASS indices during 1994-2010. The Global Macro style had the highest average annual return of 12.4% and the Event Driven style had the highest Sharpe ratio of 1.667. On the other hand, the Dedicated Short Bias style was the worst performer during this period. In line with earlier literature (Lo, 2001; Malkiel & Saha, 2005), distributions of hedge fund returns were severely non-normal, as indicated by high kurtosis and mostly negative skewness. The Jarque–Bera test on normality is rejected at 1% level in all the styles except the Managed Futures category. The non-normal distributional patterns suggest that statistical inference in linear models can biased.

It also means that it is important to conduct other types of statistical tests that do not rely on distributional assumptions, such as an out-of-sample testing, to validate hedge fund models.

<<Insert Table 2>>

Table 3 displays correlation coefficients between hedge fund style returns and three sets of risk factors. All the styles except the Managed Futures category have statistically significant correlation with equity markets returns. Fama-French factors are significant in half of the styles, while none of the styles is 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. Correlations of hedge fund style returns with the trend following factors are low. Overall, these results confirm that hedge fund strategies are not market neutral, because most of them are significantly correlated with various risk factors.

<<Insert Table 3>>

However, correlations in Table 3 provide evidence only about linear dependences between the variables. If hedge funds are nonlinearly exposed to systematic risk and the relationship is nonlinear, any correlation might significantly underestimate the relationship between the variables.[7] Given this motivation, the next section examines a range of nonparametric hedge fund pricing models that have the ability to capture nonlinear patterns in risk exposures.

4.2 In- and Out-of-Sample Tests

Next, we discuss the results of in-sample and out-of-sample performance of the models. The goal is to ascertain whether including nonlinearities leads to enhanced forecasting performance of hedge fund style returns.

As seen in the R^2 statistics in Table 4, not surprisingly all the nonlinear models outperform their linear competitors in-sample. These results indicate potential nonlinearities in risk exposures.

However, when considering performance using in-sample data, we must be cautious about any conclusions, as over-fitting is easy with nonparametric techniques. Performance statistics based on the AIC criterion are not reported here for brevity but produce similar results.[8] The two linear models from the literature, the FH7 and HL6, have similar performance to one another.

To the best of our knowledge, the FH7 model, although widely used by academics, has not been previously compared against other models. Apart from the Fund of Funds style, it

[7] For instance, correlation between any two random variables X and Y, where X is distributed normally and $Y = X^2$ is zero.

[8] Available from the authors.

outperforms the HL6 model only in the equity styles, and this outperformance can be attributed to the presence of the size factor in this model rather than to PTFS factors capturing nonlinearities.[9]

If we focus on the Managed Futures style, for which the FH7 model was originally developed, the R^2 coefficients are very close: 0.22 and 0.24 for the FH7 and HL6 models respectively. This suggests that PTFS factors do not contribute much to explaining aggregate Managed Futures returns.

<<Insert Table 4>>

Next, we turn to examination of out-of-sample performance. Table 5 reports annualized Root-Mean Squared Error (RMSE) (Panel A) and Mean Absolute Error (MAE) (Panel B) for linear and nonlinear models during the out-of-sample period from January 2004 through September 2010. Models with the lowest values of RMSE and MAE are highlighted in bold. Table 5 is one of the few examples in the literature of out-of-sample evidence of nonlinearities in hedge funds. Earlier, Amenc et al. (2010) examined out-of-sample a range of nonlinear models,[10] but did not find any evidence of their superior properties compared with simpler linear factor models.

From Table 5, we note that the nonlinear models have lower RMSE than linear models with the exception of three styles (DSB, EMN, and FoF). This result is important because it suggests that the nonlinearities driving hedge fund returns are genuine, not the result of data overfitting or an artefact of noisy data. The fact that the nonlinear models' outperformance is modest may be attributed to the short out-of-sample period, covering only five years of data; as a

[9] When we excluded size factor (SNPMRF) from the FH7 model, it no longer outperformed the HL6 model in equity styles.

[10] The authors examined the option-based factor model, Markov regime-switching model, and Kalman filter model (Amenc et al., 2010).

consequence, we believe there are not enough observations at the extremes of the return distribution where nonlinear patterns may be particularly pronounced. Nevertheless, nonlinear models perform particularly well in Managed Futures and Convertible Arbitrage styles. This is because these styles have multiple nonlinearities related to various market factors (as highlighted in section 5.1).

Unexpectedly, the popular FH7 model[11] demonstrates the highest tracking error among all the models. The FH7 model incorporates nonlinear "trend following" factors. It only outperforms the HL6 model, which exclusively incorporates linear factor exposures, 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 nonparametric models also outperform the FH7 model. A subpar performance of this model out-of-sample suggests that trend-following factors may be not relevant to other hedge fund styles besides the CTA style and even within the Managed Futures style when compared with other nonlinear models.

<<Insert Table 5>>

4.3 Nonlinearities in Individual Hedge Funds

In the previous section, we examined nonlinear risk exposures in hedge fund style indices. In this section, we extend the analysis of nonlinearities to individual funds. This is required because aggregation of hedge funds in an index might accentuate spurious nonlinear patterns or, on the contrary, dampen any genuine nonlinear patterns existing in individual funds' exposures (Diez de los Rios & Garcia, 2011). Furthermore, the search for nonlinear risk exposures in individual hedge

[11] The nonparametric analog of the FH7 model is not considered because it already contains three nonlinear factors that are supposed to capture nonlinearities in risk exposures.

funds is important because it allows tests for individual manager investment skill. A manager with genuine investment skill should not only have "passive" linear risk exposures to alternative risk factors (i.e., alternative beta) but should also produce enhanced returns through nonlinear "active risk exposures."

To analyze nonlinearities at the fund level, we fit the best linear (SLM14) and nonlinear (SGAML14) models as identified in the previous section and classify funds into linear funds, nonlinear funds, and market-neutral funds according to the type of their risk exposures.

When classifying each hedge fund, to avoid data snooping we use bootstrap to determine critical values of R^2 model fit statistics.[12] Table 6 reports percentiles of adjusted bootstrap R^2 of linear and nonlinear models fitted to 1,000 series of returns generated randomly from the standard normal, and also from the t-distributions (with one and two degrees of freedom) as well as bootstrap (with resampling) from the pooled distribution of hedge fund returns. We calculate critical values of model fit statistics as average values of the 95th percentiles across all the samples. We find that the appropriate critical value of the linear R^2 is 0.2787 for the model with 14 factors and 0.1645 for the six-factor model.[13] These results indicate a high chance of getting spurious fit when dealing with individual funds; thus, the threshold for a significant model fit R^2 should be set according to these values. It also suggests that the "reality check" procedure is warranted and necessary to minimize the risk of drawing incorrect conclusions.

[12] We use a GAM with loess smoothers as a benchmark nonlinear model because it has demonstrated lower out-of-sample tracking error than a GAM with cubic splines (see Table 5 above). The nonlinear model is fitted to the residuals of the linear model and captures nonlinear systematic risk premium that is not captured by the linear model.

[13] These values are quite high, particularly when compared with results for linear multi-factor models fitted in the literature. For instance, Titman and Tiu (2011) report a median R^2 for individual funds' regressions of 0.24 using the seven-factor Fung and Hsieh (2004b) model and 0.42 using a stepwise approach with 31 factors. These numbers are clearly not far away from R^2 generated for random regressions in Table 6.

The critical values for nonlinear 14- and six-factor models are 0.1684 and 0.1193 respectively. They are lower than for the analogous linear models, because nonlinear models capture only residual systematic variation due to nonlinear risk. The R^2 percentiles across the four distributions and three sub-periods show only small variation, suggesting that the critical values are robust to deviation from normality in hedge funds' return distributions. Also, critical values are similar to those reported in Bollen (2013).

<<Insert Table 6>>

Next, we use critical values of model fit statistics found in Table 6 to classify hedge funds into three groups: funds that show only linear exposures (Linear), funds with nonlinear exposures (Nonlinear), and funds with low or insignificant exposures to systematic risk (Neutral). In Table 7, Panel A and Panel B show the results of classification using 14-factor and six-factor models. The average values of R^2 of the linear and nonlinear models are also reported.

The table reveals several important findings. The proportion of funds with nonlinearities is 15% (see Table 7, Panel A, bottom row ["Total"], "Nonlinear" columns, "% Funds" column) and 21% (see Table 7, Panel B, bottom row ["Total"], "Nonlinear" columns, "% Funds" column), based on the 14- and six-factor models respectively. Thus, over the long run, around one-fifth of funds have significant nonlinear risk exposures. This suggests that the majority of hedge funds exhibit linear "alternative beta" (i.e., buy-and-hold) strategies, although we must be careful as it is not possible to analyze funds' short-term dynamic trading behaviour without knowing their portfolio composition. However, over the long run, we can be confident that the risk exposures of the majority of hedge funds are linear and aligned with the simple "buy and hold" exposures of alternative beta portfolios.[14]

Interestingly, 19% (Panel A: 14-factor model) and 28% (Panel B: six-factor model) of funds are neutral and have no significant risk exposures to either the 14 or six risk factors isolated in prior studies. This result is intriguing: it suggests that there are "missing factors" driving hedge fund returns. It also means that certain funds may be misclassified into the wrong style and that style gaming may be an issue for hedge funds.

In summary, over the long run many hedge funds behave like alternative beta portfolios and maintain linear exposures to systematic risk factors. Nevertheless, in every hedge fund category there are funds that exhibit nonlinearities, and they cannot be analyzed using linear multi-factor models. That is why our findings provide a clarification to the studies of Diez de los Rios and Garcia (2011) and Bollen (2013). With respect to this literature, our contribution is to show that of a third of funds classified as "zero R^2" funds in Bollen (2013), around half actually have significant risk exposures, but these exposures are nonlinear, consistent with the evidence in Diez de los Rios and Garcia (2011).

<<Insert Table 7>>

[14] In line with earlier observations at portfolio level, in directional styles (LSE, DSB, EM) there are fewer nonlinear funds than in other 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 nonlinearities in 10-15% of long-short equity funds. On the other hand, Equity Market Neutral, Global Macro, and Managed Futures styles have the highest proportion of funds without any linear or nonlinear exposures.

4.4 Performance of Funds with Nonlinearities and Persistence of Nonlinear Exposures

Finally, we examine performance of funds with nonlinearities and analyze the persistence of funds' form of exposure to systematic risk. There is prima facie evidence of investment skill among funds that have enhanced returns resulting from persistent, nonlinear risk exposures to systematic risk factors.

Different forms of exposures reflect different investment approaches. Thus, it is of great interest to investigate whether funds following more dynamic and complex strategies resulting in nonlinear payoffs outperform funds with simple linear buy-and-hold-like payoffs.

Table 8 presents descriptive statistics for the three classes of funds and Table 9 contains their performance characteristics over the 1995-2009 period. On average, the overall raw returns of nonlinear funds are 0.1% lower than returns of linear funds and 0.28% lower than returns of market-neutral funds, while featuring higher volatility. Also, the distribution of nonlinear funds' returns has higher negative skewness and higher kurtosis than the distributions of the other two classes of funds.

The risk-adjusted performance metrics in Table 9 also suggest that overall, nonlinear funds underperform linear and market-neutral funds. Nonlinear funds on average have lower Sharpe ratio (overall $\Delta Sharpe$ is -0.0673), alpha, and appraisal ratio[15] than linear funds. The difference is highly significant for alpha and appraisal ratio, but not for the Sharpe ratio.[16] Nonlinear funds

[15] Following Agarwal and Naik (2000), we define alpha as the return of the fund from a particular class within the style minus the average return of all the funds within the style in that period; appraisal ratio is defined as alpha divided by the 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.

[16] To test the difference between Sharpe ratios, we apply the Jobson and Korkie (1981) test with the correction of Memmel (2003). In this test, all the variances and covariances are adjusted for serial autocorrelation using Newey-West estimators with 23 lags.

significanly underperform linear funds in four styles out of eleven (EM, ED, LSE, FoF), and they perform better in only one style (MS).

In addition to poor performance, nonlinear funds exhibit higher negative tail risk, as measured by the expected shortfall (overall ΔES is -0.0165). The difference between the expected shortfall of nonlinear and linear funds is negative and significant in six styles out of eleven. It confirms the notion that nonlinear exposures lead to higher negative tail risk as nonlinear funds act as providers of financial insurance against distress situations.

The findings about poor relative performance of hedge funds with significant nonlinear exposure to alternative risk factors are important for the debate about fund manager skill and the value added by hedge funds. In practical terms, the whole concept of hedge fund investing can be justified if hedge funds fulfill two conditions. First, the strategies they employ are beyond the capabilites of unsophisticated investors; i.e., they cannot be easily implemented by investors. Second, and more important, these strategies generate positive incremental value to investors. While the findings in the previous sections about the presence of nonlinear features in hedge fund portfolios and some of individual hedge funds support the first condition, there is little evidence in Table 9 to confirm that these nonlinear strategies, over the long term, deliver positive performance.

These findings are consistent with studies by Chen (2011) and Peltomäki (2009), who compared performance of hedge funds which use and do not use derivatives, i.e., securities with nonlinear payoffs. Chen (2011) found that hedge fund derivatives users do not show significantly better performance than nonusers, while Peltomäki (2009) identified the complexity of derivative strategies to be positively related to weaker funds' performance and increased probability of large losses.

Another interesting result emerging from Table 9 is related to strong relative performance of market-neutral funds. They have significantly higher Sharpe ratio in most of the styles. Perhaps these funds better fit the traditional definition of a hedge fund, because they provide diversification potential (i.e., low systematic exposure) and superior performance, whereas other funds either resemble alternative beta portfolios (such as linear funds) or do not generate positive performance (nonlinear funds).

<<Insert Table 8>>

<<Insert Table 9>>

Finally, we address the issue of persistence of funds' form of exposures. Persistence is important for investors to exploit performance patterns documented above. Persistence has been examined in other studies in the context of hedge fund performance. Lack of performance persistence has been identified as one of the key problems with hedge funds, because even if some hedge funds generate absolute returns in the short run, over the long term returns do not persist (Capocci & Hubner, 2004; Malkiel & Saha, 2005).

Table 10 presents several measures of persistence. First, it reports proportions of funds with linear, nonlinear, and market-neutral exposures over the two consecutive five-year periods (known otherwise as transition probabilities). It also gives the proportion of dissolved funds over the second period (denoted in the table as "Fail"). [17] The figures are expressed as proportions of

[17] It is necessary to note that among "failed" funds, not all were actually liquidated; some funds could stop reporting due to other reasons.

the number of survived funds, while numbers in brackets give the proportions of the total number of funds in the first period. For example, out of all linear funds that existed during 1994-1998, 52% of funds survived and maintained a linear form of exposures in 1999-2003, while 35% of funds stopped reporting to the database. Total naïve persistence measures combined proportion of funds from the three classes which survived and maintained the form of their exposures. Cohen's kappa coefficient is another, more robust measure of persistence.[18] Conditional kappa measures persistence for each class of exposures, while total kappa measures overall persistence. In general, values of kappa above 0.2 indicate some level of persistence (Altman, 1990, p. 404).

As noted from the table, nonlinear exposures are less persistent than linear exposures. Only 15-25% of funds with nonlinear exposures remain in the "Nonlinear" class during both periods. The figure is much higher for linear funds, around 70-85%, and slightly higher for market-neutral funds, around 35-50%. This is confirmed by the very low and insignificant value of conditional kappa for the nonlinear class (<0.10) and much higher and statistically significant values for linear and market-neutral funds (around 0.2-0.3). Furthermore, it is noted that around 40% of nonlinear funds fail in the next period, and around the same proportion move to the linear class in the next period. This result is consistent with those earlier results where we found that nonlinear funds underperform linear funds and have higher negative tail risk. It stands to reason that after suffering poor performance compared to linear funds, some of the nonlinear funds do not survive and close down, while others alter their risk profile and become linear funds in order to remain competitive and attract assets under management. Persistence in the "Neutral" class is also understandable since these funds have the best performance relative to their peers.

[18] For more information on Cohen's kappa and how it is calculated, see the original paper by Cohen (1960) and a technical note by Rossiter (2004).

Overall, the naïve measure of persistence and the Cohen's kappa coefficient suggest persistence of funds' form of exposures for hedge funds that have "Linear" risk exposures. It appears that the active "bets" associated with nonlinear risk exposure lead to poor relative performance within a style. As a consequence of lower relative performance (and thus higher attrition rates), we believe that those nonlinear funds that survive move to the "passive" linear (i.e., alternative beta) in a desire to survive. Thus, the nonlinear class demonstrates lower persistence.

4.5 Robustness Checks

We have conducted several robustness checks to validate our results.[19] First, we used HFR indices to test linear and nonlinear models out-of-sample. Overall, the results are in strong agreement with the results documented here using TASS indices. The nonlinear model has slightly lower tracking error out-of-sample, and the result is stronger in arbitrage styles and weaker in directional styles.

Second, we examined performance of individual funds from the TASS database over the three sub-periods 1995-1999, 2000-2004, and 2005-2009. We found that during 1995-1999 and 2005-2009, the results were qualitatively similar to the results observed during the overall period 1995-2009. Nonlinear funds on average performed worse than linear funds in terms of lower risk-adjusted performance and higher negative tail risk. Funds with insignificant exposures outperformed both linear and nonlinear funds. However, in 2000-2004 nonlinear funds generated higher Sharpe ratios than linear funds, but lower than market-neutral funds. The other three measures (alpha, appraisal ratio, and ES) were not significantly different between nonlinear and linear funds. We contend that performance of nonlinear funds in 1995-1999 and 2005-2009 was influenced by crisis events such as those occurring during the LTCM debacle in 1998 and the

[19] The tables are available from the authors.

financial crisis in 2007-2008. The dot com crisis in 2000 in turn had a stronger effect on linear funds from directional styles such as the Long-Short Equity style, which invested heavily in high-tech stocks, than on arbitrage styles with nonlinear exposures.

5. Conclusion

The issue of nonlinear risk exposures is crucial for understanding the many aspects of hedge fund performance. The standard decomposition of hedge fund returns into alpha and beta components relies on the assumption that the exposures to risk factors are linear. In this study, we challenge this assumption and perform analyses of nonlinearities in hedge fund style portfolios and individual funds. We conduct out-of-sample tests of the nonlinear and linear models from the literature, including the seven-factor Fung and Hsieh (2004) model, the linear model with Hasanhodzic and Lo (2007) factors, and a stepwise linear model with 14 factors from Giannikis and Vrontos (2011).

At the portfolio level, we find that nonlinear models have a lower tracking error out-of-sample than linear models, though the result is stronger in styles implementing arbitrage strategies (Fixed Income Arbitrage, Convertible Arbitrage, and Event Driven) than in directional styles (Long-Short Equity, Dedicated Short Bias, and Emerging Markets). This is consistent with the conjecture in Agarwal and Naik (2004) of arbitrage styles providing financial insurance through short-put-like exposures. Also, the Fung and Hsieh (2004) model does not perform well out-of-sample compared to a linear model with Hasanhodzic and Lo (2007) factors. This suggests that primitive trend-following factors do not entirely capture nonlinearities in hedge fund strategies.

At the fund level, we find one-fifth of funds exhibiting significant nonlinear patterns in risk exposures over the long run. Around two-thirds of funds maintain linear risk exposures. The rest of the funds do not have significant linear or nonlinear exposures. These results mean that while in the short term hedge funds may engage in dynamic trading strategies involving complex securities, over the long run many of them behave like alternative beta portfolios.

Finally, we examine the performance of nonlinear funds and the persistence of their nonlinear form of exposures. It is found that on average nonlinear funds underperform linear and market-neutral funds on a risk-adjusted basis. Nonlinear funds tend to have higher negative tail risk too. Also, we observe that many nonlinear funds that survive over the long term alter their risk exposures and are ultimately classified as linear funds.

In conclusion, we find that most hedge funds exhibit only linear factor exposures and hence are “passive”. What’s more, such “passive” managers tend to outperform “active” managers with non-linear exposures. Our results suggest that, consistent with the notion of efficient markets removing abnormal profits, most hedge funds are “passive” and generate returns in line with their linear risk factor exposures.

Table 1 List of Models

Model	Type	Variables[1]	Variable Selection
FH7	Linear regression	FH7 factors	No
HL6	Linear regression	HL6 factors	No
SLM14	Stepwise linear regression	14 factors	Yes
GAML6	GAM using loess	HL6 factors	No
SGAML14	Stepwise GAM using loess	14 factors	Yes
GAMS6	GAM using cubic splines	HL6 factors	No
GAMS14	GAM using cubic splines	14 factors	Yes

[1] Variables are discussed in Section 3 Data

Table 2 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	Jarque-Bera test
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***

Table 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 4 In Sample Performance

The table shows R^2 coefficient for linear and nonlinear models fitted to the returns of TASS indices using a rolling window procedure during the period from January 1994 to September 2010. FH7 refers to the seven-factor Fung and Hsieh (2004) model, HL6 – Hasanhodzic and Lo (2007) model, SLM14 – 14-factor stepwise linear model, GAMS6 and GAMS14 – 6- and 14-factor GAMs using splines, GAML6 and SGAML14 – 6- and 14-factor GAMs using loess.

STYLE	**FH7**	**HL6**	**SLM14**	**GAMS6**	**GAMS14**	**GAML6**	**SGAML14**
CA	0.21	0.28	0.40	0.38	**0.69**	0.37	0.54
DSB	0.73	0.60	0.75	0.63	**0.84**	0.64	0.79
EM	0.46	0.43	0.78	0.49	**0.82**	0.48	0.80
EMN	0.26	0.24	0.28	0.27	**0.41**	0.29	0.34
ED	0.52	0.49	0.65	0.64	**0.81**	0.61	0.76
FIA	0.13	0.27	0.38	0.45	**0.71**	0.37	0.47
GM	0.11	0.20	0.37	0.25	**0.53**	0.24	0.41
LSE	0.59	0.42	0.88	0.50	**0.92**	0.45	0.89
MF	0.22	0.24	0.27	0.41	**0.50**	0.31	0.38
MS	0.16	0.31	0.39	0.38	**0.58**	0.36	0.45
FoF	0.50	0.42	0.81	0.50	**0.86**	0.47	0.83
HFC	0.45	0.39	0.75	0.47	**0.83**	0.44	0.77
Average	0.36	0.36	0.56	0.45	**0.71**	0.42	0.62

Table 5 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 linear models and GAMs fitted to the returns of TASS indices using a rolling window procedure during the period from January 1994 to September 2010. Models with the lowest RMSE (MAE) for each style are shown in bold type.

Panel A: Root-Mean-Squared Error

Style	FH7	HL6	SLM14	GAMS6	GAMS14	GAML6	SGAML14
CA	0.089	0.068	0.062	0.071	**0.058**	0.070	**0.058**
DSB	**0.096**	0.119	0.111	0.115	0.125	0.119	0.111
EM	0.089	0.075	0.058	0.090	0.067	0.072	**0.057**
EMN	0.040	**0.036**	0.039	0.038	0.049	0.038	0.040
ED	0.046	0.042	0.038	0.040	0.048	0.039	**0.037**
FIA	0.076	0.064	0.054	0.071	0.064	0.062	**0.053**
GM	0.065	0.061	0.061	0.062	0.096	**0.059**	0.060
LSE	0.064	0.045	0.035	0.059	0.037	0.048	**0.033**
MF	0.116	0.118	0.127	**0.104**	0.135	0.114	0.118
MS	0.058	0.045	0.045	0.042	0.045	**0.043**	0.044
FoF	0.047	0.041	**0.033**	0.046	0.036	0.040	0.034
HFC	0.052	0.041	0.037	0.043	0.043	0.040	**0.036**
Average	0.070	0.063	0.058	0.065	0.067	0.062	**0.057**

Panel B: Mean Absolute Error

Style	FH7	HL6	SLM14	GAMS6	GAMS14	GAML6	SGAML14
CA	0.0155	0.0126	0.0114	0.0130	0.0113	0.0125	**0.0111**
DSB	**0.0208**	0.0238	0.0215	0.0241	0.0260	0.0236	0.0212
EM	0.0202	0.0172	0.0131	0.0178	0.0134	0.0167	**0.0124**
EMN	0.0075	**0.0070**	0.0073	0.0073	0.0093	0.0072	0.0073
ED	0.0098	0.0091	**0.0080**	0.0089	0.0094	0.0087	**0.0080**
FIA	0.0119	0.0117	0.0102	0.0114	0.0116	0.0109	**0.0101**
GM	**0.0126**	0.0133	0.0130	0.0134	0.0172	0.0128	0.0129
LSE	0.0139	0.0103	0.0082	0.0127	0.0082	0.0104	**0.0078**
MF	0.0272	0.0287	0.0303	**0.0247**	0.0289	0.0280	0.0277
MS	0.0116	0.0099	0.0097	**0.0091**	0.0093	0.0092	0.0093
FoF	0.0101	0.0093	**0.0073**	0.0096	0.0073	0.0091	0.0074
HFC	0.0108	0.0097	**0.0079**	0.0095	0.0092	0.0091	0.0080
Average	0.0143	0.0136	0.0123	0.0135	0.0134	0.0132	**0.0119**

Table 6 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

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

Table 7 Fund Classification by Form of Systematic Risk Exposure

The table shows the number and the proportion of funds and the average linear and nonparametric regression R^2 for linear, nonlinear and funds with insignificant exposures (neutral) over three sub-periods, 1995-1999, 2000-2004, 2005-2009.

Panel A: 14 factors

Style	Linear				Nonlinear				Neutral			
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				Neutral			
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**

Table 8 Descriptive Statistics of Linear, Nonlinear and Market-Neutral Funds

Listed are the summary statistics for linear, nonlinear and market-neutral funds during 1995-2009. 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
	Neutral	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
	Neutral	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
	Neutral	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
	Neutral	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
	Neutral	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
	Neutral	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
	Neutral	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
	Neutral	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
	Neutral	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
	Neutral	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
	Neutral	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
	Neutral	0.0087	0.0301	0.1257	5.9526

Table 9 Performance Characteristics of Linear, Nonlinear and Market-Neutral Funds

The table presents performance characteristics of linear, nonlinear, and market-neutral (‘none’) funds during 1995-2009. Funds are initially classified in 1995, and reclassified in 2000 and 2005. 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
	Neutral	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
	Neutral	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
	Neutral	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
	Neutral	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
	Neutral	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
	Neutral	2.9300	1.3772***	2.7825	-0.0436	0.0263*	1.7002	-0.0004	-0.0009	-0.9870	-0.1652	-0.1499	-1.6032
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
	Neutral	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
	Neutral	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
	Neutral	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
	Neutral	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
	Neutral	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
	Neutral	2.1915	1.2982***	12.0570	-0.0638	0.014***	4.0555	0.0009	0.0009***	3.6563	0.0819	0.1076***	3.7854

Table 10 Persistence of the Form of Funds' Exposure to Systematic Risk

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 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. Funds dissolved during the second period are reported in column 'Fail'. 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	Neutral	Fail	Cond. Kappa	t-stat	Linear	Nonlinear	Neutral	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
Neutral	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				Naïve	Kappa	t-stat			
Persistence	0.66	0.22***	5.54				0.67	0.24***	7.27			

	1996-2000 / 2001-2005						1997-2001 / 2002-2006					
Exposure	Linear	Nonlinear	Neutral	Fail	Cond. Kappa	t-stat	Linear	Nonlinear	Neutral	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
Neutral	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				Naïve	Kappa	t-stat			
Persistence	0.63	0.23***	7.69				0.66	0.25***	9.09			

	1998-2002 / 2003-2007						1999-2003 / 2004-2008					
	Linear	Nonlinear	Neutral	Fail	Cond. Kappa	t-stat	Linear	Nonlinear	Neutral	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
Neutral	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				Naïve	Kappa	t-stat			
Persistence	0.61	0.17***	6.81				0.58	0.2***	8.16			

	2000-2004 / 2005-2009						Overall					
	Linear	Nonlinear	Neutral	Fail	Cond. Kappa	t-stat	Linear	Nonlinear	Neutral	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
Neutral	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				Naïve	Kappa	t-stat			
Persistence	0.56	0.13***	5.30				0.62	0.19***	17.66			

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